PLAYER POSITION DETECTION AND MOVEMENT PATTERN RECOGNITION FOR AUTOMATED TACTICAL ANALYSIS IN BADMINTON

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A thesis submitted in fulfillment of the requirements for the degree of
Doctor of Philosophy

September, 2017

"Know the enemy and know yourself; in a hundred battles you will never be in peril."

—Sun Tzu, The Art of War

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Abstract

Increased popularity and funding for international sporting competitions have made monitoring and maintaining a high level of athletic performance paramount. Scientists have been employed to assist in performance evaluation and maintenance, while various technological tools have been developed to assist the sports scientists. Sports tactical performance is monitored by a subset of these scientists called tactical analysts. Although significant technological advances have been made in the sports domain, application of technology in automating tactical analysis remains under explored. This thesis investigates tactical analysis in the sport of badminton as well as the requirements for developing a comprehensive methodology for its automation. Automated latent tactical information gathering, extraction of quantifiable measures that describe tactical performance (tactical indicators), analysis of these tactical indicators and presentation of analyzed data to domain experts were identified as the requirements for automation.

Automated latent tactical position data was gathered from video footage captured at international badminton tournaments using an image processing algorithm. The algorithm is capable of detecting and handling the occlusion situation, based on unique circumstances observed when two badminton players on opposite sides of the net occlude each other. Accuracy of player position detection was validated using video footage captured at multiple international badminton tournaments.

Next, this thesis quantifies a tactically relevant two dimensional cellular space on a badminton court, similar to the cellular space used by domain experts. The borders of the tactical cells were experimentally identified and an automated method called dynamic window annotation was developed to represent latent position information on this cellular space. The cellular space provides a tactical context to latent position information, allowing the extraction of badminton tactical indicators in the form of numerical strings. The ability

of these tactical indicators to describe badminton tactics was discussed through data from an international badminton match.

K nearest neighbor classification was used to assign collections of tactical indicators to ten tactical movement groups, allowing their underlying tactical implications to be understood efficiently by a domain expert. Results of the classification demonstrated the ability of the overall method in tactical analysis, as well as deficiencies of classification in adapting to domain requirements due to the need for training data. A similarity based grouping method to assign tactical indicators to the same tactical movement groups was evaluated. This method demonstrated comparable results with the best classification approach and is capable of negating the requirement for training data.

Finally, the grouped tactical information was visualized on a radar plot for visual examination. The ability of this representation for efficient tactical comprehension was demonstrated through two case studies.

The individual components presented in this thesis were evaluated against badminton domain experts and indicate their ability to automate individual steps in badminton tactical analysis. The case studies demonstrate the ability of the combined approach to comprehensively automate badminton tactical analysis.

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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Date:

List of publications

Conference papers

1. **Weeratunga, K.**, How, K. B., Dharmaratne, A., & Messom, C. (2014, December). Application of computer vision to automate notation for tactical analysis of badminton. 13th International Conference on Control Automation Robotics & Vision (ICARCV), 2014 (pp. 340-345). IEEE.

2. **Weeratunga, K.**, Dharmaratne, A., & How, K. B. (2017, June). Classification of Spatio-temporal data represented as multisets for tactical profiling in badminton. 2nd International Conference on Image, Vision and Computing (ICIVC), 2017 (pp. 979-984). IEEE.

3. **Weeratunga, K.**, Dharmaratne, A., & How, K. B. (2017, July). Application of computer vision and vector space model for tactical movement classification in badminton. IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2017 (pp. 132-138).

Journal papers (*under review*)

1. **Weeratunga, K.**, Dharmaratne, A., & How, K. B. Similarity Based Supervised Grouping of Movement Data for Tactical Profiling in Badminton. Pattern Analysis & Applications.

2. **Weeratunga, K.**, Dharmaratne, A., & How, K. B. Understanding tactical movement patterns. Human Movement Science.

Acknowledgements

First and foremost I want to express my deepest gratitude to my main supervisor Dr. Anuja Dharmaratne for her support and guidance. Ever since you took over during my second year, you have been way more than a supervisor and have treated me like a son. I am forever grateful. I would also like to express my appreciation for my associate supervisor Mr. Khoo Boon How. You have been a friend for many years and a valuable guide throughout the past four years. I also thank my main supervisor during the first year Professor Chris Messom, my external Supervisor Dr. Yeo Wee Kian, as well as Dr. Sylvester Orimaye, Dr. Hisham Jaward, and Dr. Alpha Agape for your constructive feedback and advice during various parts of my candidature.

Secondly, I wish to express my gratitude to the two institutions that supported this research project. The academic and administrative staff of Monash University provided support in various forms during my candidature. I especially wish to mention the late Siri, who showed kindness, understanding and support to me during her time at Monash. The National Sports Institute of Malaysia through its staff, athletes and coaches provided a large amount of guidance to this project. The research was facilitated through access to their badminton video libraries as well as badminton tactical analysts.

There were many friends who encouraged and supported me during my candidature, and a few of these require mentioning by name. Manju sat on my left, became one of my best buddies and taught me a great many things. I thank you for all the technical knowledge you have imparted on me and for remaining a valuable academic guide after your graduation. Tes replaced Manju on my left and kept me sane through some stressful times and has become a great friend. I wish you all the best in completing your research. I also thank Yakub, Kasun, Najini, Dilukshan and Anirudh for all your technical as well as non-technical support at various points during the past four years.

Finally, none of this would have been possible without the love and support of my family. Words cannot express how grateful I am to my parents. Amma and Thaththa, I am forever indebted for your unconditional love and all you have sacrificed for me. I would not have even made it to the start of this journey without you two. To my sister Hashini, I thank you for sharing the load of responsibilities back home. You have helped to keep my mind at ease, especially through some trying times during the past couple of years. Most importantly my wife Chaminie, without you this journey would not have happened. You encouraged me since my application process, tolerated my constant absences for four years, and shouldered the bulk of household chores so that I would not be burdened. You stood by my side and remained resolute in your support for my work despite any discomfort caused to yourself. You are amazing. I love you.

Kokum Weeratunga
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2017

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CHAPTER 1

Introduction

1.1 Background on sports, science, and technology

Sport is an activity involving physical exertion and skill in which an individual or team competes against another individual or team for entertainment [1]. Sporting competitions have become an integral part of society [2], where it has been shown to provide financial benefits to the community [3–5] as well as psychological benefits to individuals [6, 7]. In return, the community has invested large amounts of funding on sporting competitions and infrastructure [8, 9]. The craving for sporting competitions has grown steadily throughout history [10], culminating with the modern age where the advent of technology has brought sports to the homes of fans [11] through television and online media.

The professional sporting industry has benefited from this increased popularity and accessibility to spectators, where the industry has become a lucrative business with dramatically increased revenue [12]. Organizing sporting events and professional sporting teams are valued in billions of dollars. For example, the London Olympic Games in 2012 was reported to cost 15 billion [13], while the Qatar Football World Cup in 2022 is estimated to be 16 billion [14]. The Los Angeles Clippers basketball team was sold in 2014 for 2

billion dollars [15], while the soccer club Manchester United has an estimated value of over 3 billion in 2017 [16]. Professional athletes have reaped the benefits of their labor as well, with basketball player Stephen Curry expected to make over 80 million dollars in the next 12 months [17], and tennis player Roger Federer having earned over 65 million during the 12 months ending in June 2016 [18]. While athletes naturally have a desire to excel in their respective sport [19], these high value teams and athletes also have an invested financial interest in improving and maintaining their athletic performances.

The task of sports performance maintenance has traditionally been entrusted to a coach, who is responsible for observing athletic performance during competitions, identifying key deficiencies that can be improved, and organizing a training plan to address these deficiencies [20, 21]. However, in modern professional settings, the role of a coach has expanded to be an organizer [20], responsible for managing the training and competition environments, the social and psychological development of athletes, developing and maintaining a relationship with funding agencies, etc., [21]. In order to cater to this growing demand, the coaching structure has expanded substantially [22] to include assistant coaches, trainers, doctors and sports scientists [23]. Many nations at present possess a modern sports science support system [24–30] where sports scientists and medical practitioners are considered an integral part of a successful sporting structure [31]. Consequently, present day elite athletes have become increasingly reliant on sports science expertise and guidance, in order to maintain and enhance performance [32].

Sports scientists evaluate four main types of athletic performances; physical, mental, tactical and technical [19]. This is in fact similar to a traditional coach that observes and evaluates athletic performance, although, the sports scientists follow a systematic approach in quantifying the performance and subsequent objective analysis [33]. These systematic approaches involve measurement and analysis of performance indicators, which are quantifiable measures that describe a type of performance [34]. For example, maximum heart rate or oxygen intake [35] can be considered an indicator of physiological performance, while a player passing a ball can be considered a tactical indicator [36].

As with many other domains [37], the work of sports science experts has also been influenced by recent advances in engineering and computer science. Technological systems have been developed to enhance the efficiency and accuracy of gathering performance information [38–41]. Technology has also enhanced the efficiency of feedback to athletes, where in some cases, information on their performances is provided almost instantaneously [42]. The influence of technology and science in sports [43, 44] is expected to enhance athletic performances to previously unimaginable levels [45].

The increasing popularity [10, 11], funding [8, 9, 12], and the desire to maintain a high level of athletic performance [19], has resulted in the acceptance of scientists in the sporting community [22, 23]. The systematic approaches implemented by these scientists [33] have also presented technologists (engineers and computer scientists) with an opportunity to enter the domain of sports performance monitoring. This union of athletes, scientists and technologists, has created a unique convergence of experts from both the physical and intellectual domains, and provides intriguing avenues for scientific and technological exploration. This thesis documents the development of such a technological solution to assist sports scientists working with elite professional athletes.

1.2 Focus of the thesis

The focus of this thesis is on the sport of badminton and the tactical analysts engaged with this sport at the highest level of international competition.

1.2.1 Badminton

Badminton is the second most popular sport in the world in terms of participation, after soccer [46–48]. The majority of this participation is concentrated in Asian countries [48] such as China, South Korea and Malaysia, where it is considered the number one sport [49]. This popularity, especially in the Asian region, and its place as the number one sport in Malaysia, makes badminton the ideal sport for focusing on in this research.

There are five disciplines in badminton; Men's singles, Women's singles, Men's doubles, Women's doubles, and Mixed doubles. Men's singles discipline has been the most popular in Malaysia, due to the dominance of the athlete, Datuk Lee Chong Wei. Because of this, work documented in this thesis focuses on the singles discipline of badminton. The assumptions, experiments and evaluations, have been conducted with respect to singles badminton.

1.2.2 Tactical analysis

As explained previously, the four major types of performance evaluated by sports scientists are physical, mental, tactical and technical [19]. Of these four, physical performance evaluates aspects such as speed, strength, power, etc., [50]. Technical analysis evaluates the way in which a sporting action is performed [51]. While both of these performance types can be evaluated during a competition, improvements in performance can only be attained through an extensive training regime. Mental performance evaluates the psychological makeup of athletes [52], and similar to technical and physical performance, training to enhance mental performance is conducted following the completion of competition, or at best in between matches during a competition [53].

This is not the case with tactical performance. In the high pressure competitive environments of sports [54], athletes interact through mutual anticipation [55], where tactical movements are initiated to counteract the opponents' moves, based on decisions deduced through sensory information [56–58]. The ability to deduce optimal solutions, based on sensory information, is dependent on the availability of information on past events [54, 58, 59]. Comparison of past events against new sensory information provides a basis for accurate anticipation and formulation of optimal counter tactics. Hence, tactical analysis and feedback provides an immediate impact on the outcome of a match. Therefore, tactical analysis can be considered of more immediate significance, in comparison to the other three types of performance, provided the tactical analysis and feedback can be performed during the match.

1.2.3 Domain experts

Despite the relative popularity of the sport, badminton tactical analysis remains an under explored domain. Automated tactical data analysis has not been explored at all. Due to this lack of published literature, badminton domain expertise and feedback was sought at various points of this study. Additionally, the proposed automated approaches have been evaluated against the same task performed manually by a domain expert.

The domain expert in this case was the tactical analyst for the Malaysian national badminton team. The Malaysian badminton team is, at present, ranked number five in the world, and has traditionally been one of the best badminton teams in the world. The tactical analyst has over five years of experience working with this team, and has been employed full-time in this role since 2009.

1.3 General problem identification

The discussion in Section 1.2 identifies an appropriate direction for exploration in the development of a technological solution to assist sports scientists. The overall goal can be stated as the automation of tactical analysis in badminton. In order to achieve this, the following study areas were identified.

1.3.1 Automated data gathering

As explained previously, sports scientists have implemented a systematic approach [33] of gathering and objectively evaluating features related to athletic performance. Hence, the first step in the development of a comprehensive automated approach for tactical analysis would be automated data acquisition.

The most common approaches used to automatically gather information on athletes have been through sensors placed on the body of athletes [60–62], within equipment used by the athletes [63], motion capture systems [64], video cameras [38, 65–67] as well as the combinations of multiple approaches [68]. The appropriateness of these approaches

depend on the specific sport. For example, in soccer, the size of the playing field is extremely large. Hence, it would be an unrealistic expectation to use a single fixed video camera without the ability to pan and zoom to capture information on the entire field. In international swimming, the hydrodynamic drag requires to be minimized in order to optimize performance. Therefore, the placement of a large sensor on the swimmers body would impede performance. Tactical analysis at international badminton tournaments require information on all players involved in a match. However, it is unreasonable to expect an athlete to allow sensors to be placed on them by opposing teams. As such, the most appropriate method for data gathering is through video footage. Hence, a method suitable to gather information from video footage at international badminton tournaments must be identified.

1.3.2 Contextual data representation

The frequency and sensitivity of data acquisition is limited by the data acquisition method. For example, if information on the position of an athlete is gathered through sensors placed on their body, position information may be gathered every millisecond, at an accuracy of a centimeter. Similarly with video footage, data may be gathered at a frequency equal to its frame rate. In contrast, the manual data gathering of a sports scientist could never be as frequent or as accurate. Hence, the quantity of data gathered through automated means is expected to be large.

Providing a contextual structure to this glut of data allows the extraction of important or useful portions, while eliminating the redundant data points [69]. This contextual structure is exemplified in the classification of information by tactical analysts as latent information and tactical indicators [36]. In this classification, high level information such as position or action of players are considered latent, while low level descriptions such as a player paths, or the action of passing a ball are considered tactical indicators.

Hence, a contextual representation must be provided to the large quantity of latent information gathered through automated means. This would allow tactical indicators to be automatically extracted for use by the tactical analysts.

1.3.3 Data analysis

Large quantities of information has generally been considered advantageous to decision makers [70]. However, an information saturation point can be reached, beyond which, additional information becomes redundant, and in some cases a hindrance to human decision makers [71–73]. Data analysis methods allow a large quantity of information to be inspected, allowing underlying patterns to be identified. In sports tactical analysis, large databases of tactical indicators are analyzed to identify underlying tactics and strategies. The results of this analysis support tactical changes and developing counter strategies. Hence, the raw tactical indicators require to be analyzed in order to understand their underlying tactics and strategies.

1.3.4 Applicability and adaptability in the domain

The developed approach to automatically gather player position information, extract and analyze tactical indicators, is required to be applicable and adaptable in the domain of elite badminton. The requirements of sports scientists, the demands of elite professional athletes and coaches, in both training and competition environments, as well as the domain specific limitations and restrictions at these environments must be sought and considered at each step.

1.3.5 Tactical data visualization

Correct and efficient interpretation of information provided to a human decision maker, requires the decision maker being trained in the representation of this information [74]. Hence, comprehension is enhanced when information is provided in a manner that is

familiar to the decision maker [75]. This is exemplified in tactical analysis of tennis [76], squash [77], and soccer [78], where tactical position and trajectory information have been analyzed and discussed with respect to the field of play, allowing efficient comprehension by an individual familiar with the respective sport.

Hence, the underlying tactics and strategies should be visualized in a manner that allows efficient comprehension by a domain expert.

1.4 Research questions

The overall objective of the research can be stated as; *the development of a comprehensive automated approach for tactical analysis in badminton.* The above discussion identified several study areas involved in achieving this objective, through which the following research questions were identified.

1. How can tactical information of badminton players be automatically gathered at international tournament environments?

2. How can tactical indicators be extracted from the automatically gathered tactical information?

3. Can the tactical indicators be analyzed in order to easily comprehend their underlying tactics?

4. Can the analysis method easily be adapted to domain requirements in badminton tactical analysis?

5. Can the underlying tactics and strategies be visualized in a manner that allows efficient comprehension?

1.5 Overview of the thesis

The above mentioned research questions have been addressed in this thesis.

1.5.1 Flow of work

The flow of work documented in this thesis is illustrated in Figure 1.1. First, a method to automatically gather badminton player position data (latent information related to tactics) from video footage was developed. Second, a contextual representation was provided to this latent information allowing tactical indicators to be extracted. Third, a method was proposed to analyze these tactical indicators in a manner that is familiar to badminton domain experts. Finally, a fundamental issue that could affect the adaptability of the overall approach at international tournament environments was addressed. The resulting comprehensive approach allows the generation of player tactical profiles which can be examined efficiently by a badminton tactical analyst.

Figure 1.1 Flow of work in the thesis.

1.5.2 Organization of chapters

The chapters of this thesis are organized as follows. Chapter 2 provides a comprehensive review of literature while Chapter 8 concludes the report. Chapters 3 to 7 each address a research question presented in Section 1.4.

Chapter 2: *A perspective on sports and tactical analysis: A review of literature*

This chapter provides insight on sports tactical analysis through a review of relevant literate. This review focuses on the fundamentals of sports performance analysis before focusing on the details of manual and automated approaches.

Chapter 3: *Automated data gathering: An image processing approach for player position detection*

This chapter addresses the first research question in order to automate tactical data gathering. An automated method is proposed and evaluated, in order to automatically gather latent position information from badminton video footage.

Chapter 4: *Contextual data representation: Extracting tactical indicators*

This chapter addresses the second research question in order to provide a tactical context to the latent information. Tactical regions on the badminton court are experimentally quantified. An automated method is proposed to annotate latent information and extract tactical indicators.

Chapter 5: *Data analysis: Classification of tactical indicators*

This chapter addresses the third research question in order to analyze tactical indicators. A machine learning approach is proposed and evaluated in order to understand the underlying tactics of the tactical indicators.

Chapter 6: *Applicability and adaptability in the domain: Approach to eliminate the reliance on training data*

This chapter addresses the fourth research question in order to ensure adaptability of the analysis method in the domain. An enhancement to the machine learning approach is proposed and evaluated in order to enhance its adaptability.

Chapter 7: *Tactical data visualization: Player tactical profile generation*

This chapter addresses the fifth research question in order to identify the best method for tactical data visualization. Several visualizations are evaluated before identifying the most suitable for badminton tactical analysis.

Chapter 8: *Conclusion*

This chapter reviews the work reported, provides a summary of findings, and proposes directions for future exploration.

1.6 Contributions of the thesis

This section describes the contributions documented in the following chapters of this thesis.

1. **Chapter 2: -** A comprehensive literature review was completed on performance analysis of sports. This review provided the foundation for work presented in subsequent chapters. This chapter highlights the following.

   (a) Tactical analysis is a subcategory of sports performance analysis where performance analysis is founded on the fundamentals of notational analysis. These fundamentals have been adapted in automated tactical analysis where automated latent tactical data gathering, extraction of tactical indicators, subsequent analysis and presentation were identified as the steps involved.

   (b) The types of tactical indicators used in notational analysis were reviewed in order to identify tactical indicators to be used for the problem at hand.

   (c) The automated approaches used for data gathering in sports and specifically badminton were reviewed in order to identify their advantages and disadvantages, as well as gaps in the literature.

   (d) The automated approaches used for tactical indicator analysis in sports were reviewed in order to identify their advantages and disadvantages, as well as gaps in the literature.

2. **Chapter 3: -** This chapter contributes the following in order to automate latent tactical information gathering in badminton.

   (a) Develops an image processing algorithm for player position detection from video footage captured at international badminton tournaments.

   (b) Examines occlusion situations in badminton and identifies features in player trajectories.

   (c) Develops an occlusion handling approach based on these features in order to identify individual player positions.

(d) Experimentally validates the player position detection using video footage captured at international badminton tournaments by a competing team.

3. **Chapter 4: -** This chapter contributes the following in order to extract tactical indicators from latent tactical information.

   (a) Identifies the optimal tactical cellular representation for badminton singles.

   (b) Experimentally determines the borders of this cellular space.

   (c) Identifies errors in annotating latent position information on this cellular space due to marginal fluctuations in player position detection.

   (d) Proposes an automated annotation method to negate these errors (dynamic window annotation method).

   (e) Evaluates the ability of the quantified tactical cellular space and dynamic window annotation method to replicate the intuitive manual annotation of a domain expert.

   (f) Proposes a symbolic representation for badminton player trajectories on this cellular space and extracts frequently repeated trajectories (tactical indicators).

4. **Chapter 5: -** This chapter contributes the following in order to analyze the badminton tactical indicators (frequent trajectories).

   (a) Examines the characteristics of classification algorithms and identifies the best approach for use at international badminton tournaments.

   (b) Defines ten classes for classification of frequent trajectories.

   (c) Proposes three representations for frequent trajectories and appropriate similarity measures for each.

   (d) Experimentally identifies the optimum parameters for classification with each representation.

   (e) Evaluates the best representation and similarity measure for classifying frequent trajectories.

5. **Chapter 6: -** This chapter contributes the following in order to enhance the analysis method in the previous chapter.

   (a) Proposes grouping frequent trajectories based on their similarity with a trajectory representing each group.

   (b) Defines representative trajectories for classes (groups) defined in the previous chapter.

   (c) Modifies similarity measures from the previous chapter based on the characteristics of representative trajectories.

   (d) Experimentally identifies the optimum parameters for grouping with each representation.

   (e) Evaluates the best representation and similarity measure for grouping frequent trajectories.

   (f) Evaluates the ability of the best grouping approach to replicate the performance of the best classification approach from the previous chapter.

6. **Chapter 7: -** This chapter contributes the following in order to identify the best method to visualize the analyzed badminton tactical indicators (classified frequent trajectories).

   (a) Examines methods for tactical data visualization.

   (b) Identifies patterns in the classified frequent trajectory data.

   (c) Proposes a normalization method based on these patterns in order to allow efficient visual comparisons.

   (d) Proposes the visualization of this data on a radar plot and comparisons against tactical movements represented on a badminton court.

   (e) Illustrates badminton tactical analysis using this visualization and two example case studies.

CHAPTER 2

A perspective on sports and tactical analysis: A review of literature

The inclusion of sports scientists and technologists in the professional sports domain have created an intriguing ecosystem of intellectual experts and expert physical performers. This combination creates a new and interesting avenue for scientific and technological exploration. This chapter provides a perspective on this ecosystem, focusing on technology for one group of sports scientist called tactical analysts.

2.1 Introduction

With increasing popularity and monetary gains in international sports, performance maintenance has become increasingly important. Sports scientists have been employed to assist in performance evaluation, and subsequently, technologists have been employed to develop tools for the sports scientists. This chapter comprehensively examines badminton tactical analysis while focusing on the overall objective of the thesis, which is developing a comprehensive automated approach for tactical analysis in badminton.

First, Section 2.2 focuses on the fundamental aspects of sports tactical performance analysis in order to gain a comprehensive understanding of the underlying principles. Second, Section 2.3 focuses on manual approaches used in tactical analysis in order to understand the types of information used for tactical analysis. Finally, Section 2.4 focuses on automated approaches that can be used in automating badminton tactical analysis. The discussion includes a multitude of sports, and focuses on badminton where the available literature makes it possible.

2.2 Fundamentals of sports tactical analysis

Sports science is an applied science of sporting behavior [79]. Hence, most if not all sports scientists engaged with the task of analyzing sporting behavior can be called performance analysts in sports. These sports scientists evaluate four key aspects of sporting performance; physical, mental, tactical and technical [19]. Therefore, tactical analysts and tactical performance analysis is a sub category of sports scientists and performance analysis (Figure 2.1). While the methods of analysis and the types of information used for tactical performance analysis may differ in comparison to the other three types of performance analysis, the fundamental principles involved are common to all four. As a result, the published literature on these fundamentals concentrate on performance analysis as a whole and are reviewed in this section with respect to, what is performance analysis? why do performance analysis? and how to do performance analysis? The discussion of these

fundamentals are directly applicable to tactical performance analysis, unless otherwise stated.

Figure 2.1 Sub-categorization of performance analysis.

2.2.1 What is performance analysis?

An introductory overview on performance analysis [80, 81] describes performance analysis as, the evaluation of an athletes' or teams' performance during a competition itself. This performance can be observed in real-time during the game or through observing video footage recoded during the game. For example, physiological information can be directly measured during competition or immediately after the competition, such as heart rate, blood lactate and perceived exertion [82, 83], and can be analyzed to evaluate physical performance.

The definition on performance analysis has been expanded to include evaluation of qualitative or perceived information gathered through self-reporting, provided the information is gathered in reflection of the performance during a game. This is often applicable in evaluating mental performance or an athletes' mental state, where information is gathered through self-reporting by athletes using standardized reporting methods [84, 85].

Finally, the definition has also been expanded to include analysis performed through laboratory experiments. This is applicable in technical evaluation of actions [86, 87], such as kicking a ball or running, with the intent of optimizing this action. In such cases, precise information on the human body, such as joint angles or stride length are required, which can only be gathered through sophisticated laboratory equipment.

Based on the overview on performance analysis [80, 81], tactical analysis focuses on the strategies (game plan) and the tactical decisions. Strategies refer to a broader plan based on the evaluation of an opponents' strengths and weaknesses. Such a plan aims to limit these strengths and exploit weaknesses in order to defeat the opponent. For example, the analysis of team formation in soccer [78] provides insights to the strategy of a team that was formulated prior to the start of the game, and implemented during the game. In contrast, tactical decisions are made by athletes during the game, based on the opportunities and risks available at that moment. For example, the analysis of passing and shots on goal in soccer [88] allows the understanding of player and team behavior in crucial situations of a game. Hence, the information that is required for tactical analysis can be gathered from the game in real-time or from video footage.

2.2.2 Why do performance analysis?

The same overview on performance analysis [80, 81], and an introduction to notational analysis of sports performance [89, 90], describes the main objective of performance analysis as, providing a method for evidence based decision making for coaches and other decision makers in sports. In the past, subjective analysis of performance has been conducted by coaches and physical educators. However, the ability of these decision makers to recall events that occur in a game is limited [91]. An objective method of annotating performance information allows subsequent analysis and informed decision making [33]. The role of such information is illustrated in Figure 2.2, where objective performance information assists in the planning of training to improve performance.

Figure 2.2 Schematic diagram of the coaching process, reproduced from [89].

While the illustration indicates the usefulness of this information for training, the information can also be applied in game situations to enhance performance, provided the aspect of performance can be enhanced in a short amount of time. This is the case with tactical analysis where information on strategies and tactical decisions can be evaluated while the game is in progress, and used to enhance tactical performance during the remainder of the game. For example, the analysis of team formation in soccer [78] provides information on the implementation of a strategy to the coach. The information tells the coach if the strategy is being implemented as expected and if one or more players are performing outside of the team strategy. This may assist the coach in providing instructions to his/her players, as well as replacing certain players through substitutions. Similarly, the analysis of passing and shots on goal in soccer [88] provides information on tactical decisions made by players during a game. If a player is passing in situations suited for shooting on goal, or vice versa, the player can be instructed to correct his/her actions or substituted.

2.2.3 How to do performance analysis?

At its most fundamental, performance analysis can be considered notational analysis [80, 81]. In fact, notational analysis was such an integral part of the performance analysis

process that the term "notational analysis" was used to describe performance analysis through its infancy in the 1980s and the early 90s, before the term "performance analysis" was adopted by the community [79, 81]. This change in terminology was a result of manual annotation losing its importance in the process of performance analysis, first, due to computerized annotation methods, and later, automated methods of gathering performance related information [81]. While technology has had its impact in the performance analysis community, the fundamentals of notational analysis remain the foundation upon which modern performance analysis is developed. Hence, a clear understanding of how notation analysis is performed, and its adaption for use with technological approaches is required.

A schematic flow of the notational analysis work is illustrated in Figure 2.3. Notional analysts gather data using a data "gathering system", which is then analyzed using a "processing system". The results are often evaluated by the same notational analysts and provided to the coach or athlete. The data "gathering system" and the "processing system" performs an important function in this flow, along with the tactical analysts themselves.

Figure 2.3 Schematic flow of a notational analyst's work, modified from [79].

2.2.3.1 Data gathering

Notational analysis involve manually annotating the most important aspects of performance in order to provide an abstract view of the sport [80]. The data gathered through this manual

annotation are called performance indicators. A performance indicator is a quantifiable measures describing a type of performance [34]. The first task in performing notional analysis is the identification of performance indicators to be gathered (the most important aspects of performance) [92]. The type of performance and the aspect of the performance to be evaluated as well as the available processing system and analysis methods must be carefully considered. This selection of the most important aspects is especially important in manual notational analysis, as the annotation is performed by a human, with limited capabilities to annotate fast paced events in sports.

The fundamental aspects of gathering performance indicators have not changed with the advent of technology, although, the method of gathering has improved. Computerized annotation allows a human to perform faster annotation, and therefore, gather larger quantities of performance indicators [41]. Automated data gathering through computer vision and motion tracking has enhanced this ability further, allowing performance indicators to be gathered without the need for manual annotation [80].

The performance indicators that describe tactical performance (strategy and tactical decisions) are called tactical indicators. For example, in soccer, the tactical indicators can describe passing, pace of attack, length of passes, shots, etc., [34]. An evaluation of trends in tactical analysis [36] concluded that all tactical indicators can be classified to three main groups. In this classification, high level information such as game task (action), space (position), and time, are considered latent, while low level descriptions such as a player path, or the action of passing are considered tactical indicators. Table 2.1 illustrates these groups as depicted in an example in [36].

Table 2.1 Example of latent information and tactical indicators in soccer, extracted from [36].

Latent Variables	**Space (Place of action)**	**Time (Action time)**	**Game task (Type of action)**
Tactical Indicators	Effective play space Path of player movement Path of ball circulation Player action zone	Frequency of events Individual and team pace Time of ball possession	Interception Turnovers Passes Shot on target

This classification and the concept of latent tactical information is an interesting development, and is especially important when examining the convergence of tactical performance analysis and automated methods for data gathering. In traditional notional analysis, data gathering refers to the manual process of annotation tactical indicators. As explained previously, the decision on which tactical indicators to be gathered is important [92]. If the annotation is to be performed during a game in real-time, an optimal number of tactical indicators to be gathered by human tactical analysts must be identified.

Consider a simple example where the tactical analyst manually annotates the landing position of the ball during a tennis service. It can safely be assumed that the tactical analyst would chose to mark the general region of the tennis court on which the ball landed. Hence, this task of directly annotating the tactical indicator requires one annotation per service and can be performed by a human in real-time. If the same data is gathered through an automated tracking approach, for example ball tracking through video capture, the position of the tennis ball would be gathered multiple times a second. Therefore, the tactical indicator (landing position of the tennis ball) must be extracted from latent information (position of the ball). Manual annotation would not annotate such latent information, as it is a waste of manpower, and would instead directly annotate the tactical indicator.

In the schematic flow of notational analysis (Figure 2.3), the "gathering system" results in a collection of data (performance indicators). However, in automated data gathering latent information is collected. The tactical indicators are to be extracted from this latent information, and this extraction can be considered a part of the data "processing system". However, a much more sensible and less confusing approach would be to equate the "gathering systems" of both notational analysis and automated data gathering. This can be achieved by including automated latent information gathering and tactical indicator extraction as parts of the "gathering system"

2.2.3.2 Data processing

Data processing involves the analysis of tactical indicators and the presentation of results in order to understand their tactical implications. However, neither of these tasks utilize an approach that can be considered standard or fundamental.

Tactical indicator analysis

The tactical indicators are analyzed depending on the aspects of tactics they describe. For example, annotation of tactical indicators related to action (type of shot) and position (position on court) in squash, allows to evaluate the frequency of a shot occurring at a particular position on the court [93]. Annotation of two performance indicators related to action in soccer (passing, shot on goal), allows to evaluate the patterns of goal scoring with respect to the number of passes before a shot on goal [88].

Computerized methods of annotation can result in large quantities of tactical indicators. Mathematical models can be used to analyze these large databases and describe the tactical structure of a sports [41]. Approaches based on machine learning can be developed to automatically analyze and identify similarities in tactical indicators, allowing comparison based on similarity rather than discrete tactical indicators. For example, large tactical indicator databases on movement patterns of a single athlete [77], or positional structures of multiple players on a team [94], can be automatically classified to a small, manageable number of groups. These groups could represent a norm of the game, such as moving to the net in tennis or an attacking player formation in soccer.

Tactical data presentation

The results of tactical analysis has traditionally been presented as a table of numerical values or standard line and bar graphs. For example, in the previously mentioned analysis of squash [93], three tables of numerical values on tactical performance are provided. Similarly in soccer [88], four line graphs, three bar graphs, two tables and a scatter plot illustrates the results. While this is suitable for scientific understanding, it can be safely

assumed that a coach or an athlete would not be able to efficiently comprehend this scientific information. This further highlights the importance of the tactical analyst in the schematic flow of notational analysis (Figure 2.3).

This trend has continued in developing tactical performance profiles using large quantities of tactical indicators gathered at multiple matches [95, 96]. A slightly different approach for data presentation is used in developing tactical performance profiles for tennis [97]. The numerical tactical information has been presented as a table, although a visual representation in the form of a radar plot has been proposed. This representation has multiple advantages. First, the overlays of multiple profiles allow visual comparison against each other. Second, the shape of the plot allows efficient comparison of individual tactical indicators against each other.

Another form of visual representation has been the representation of spatio-temporal tactical information on the field of play [76–78]. This provides an advantage in comprehension where a domain expert would be able to easily identify the tactical significance of movements.

2.2.4 Summary

Performance analysis evaluates the performance of an athlete or team during the performance itself. Tactical analysis is a sub category of this where the evaluation focuses on tactical performance (strategy and tactical decisions). Performance analysis provides a method for evidence based decision making through systematic gathering of performance indicators and subsequent analysis. This process of performance analysis is based on the fundamentals developed in notional analysis.

With the advent of technology, the schematic flow of performing notational analysis in Figure 2.3 can be modified to provide a clear illustration of performance analysis using automated data gathering and analysis methods. Figure 2.4 illustrates these modification. The automated gathering system performs the tasks of gathering latent information and extracting tactical indicators. The resulting tactical indicator database can be automatically

analyzed for complex interactions, allowing to extract patterns and trends in match play. This information on patterns and trends can then be presented to a tactical analyst, followed by a coach or athlete.

Figure 2.4 Schematic flow of performance analysis with automated data gathering and processing.

2.3 Manual notational analysis

The previous section discussed the fundamentals of performance analysis, providing insight into what is performance analysis? why do performance analysis? and how to do performance analysis? It was evident that the fundamentals aspects of performance analysis are founded on manual notational analysis. Automated approaches for tactical

analysis expand on these fundamental steps. The types of tactical indicators, their gathering and subsequent analysis play an important role. Therefore, a detailed understanding on the types of tactical indicators used in tactical analysis is a necessary precursor, before concentrating on the focus of this thesis; automated tactical analysis of badminton.

This section reviews published literature on manual notational tactical analysis in detail. Due to the lack of published work on badminton tactical analysis, the discussion focuses on team sports and racket sports, before finally examining badminton.

2.3.1 Team sports

Published literature on manual tactical analysis of three popular team sports, soccer, basketball, and field hockey, were reviewed.

2.3.1.1 Soccer

A key component of soccer is passing and scoring goals, and hence, the tactical play during this situation has been evaluated often. Passing was evaluated as a tactical indicator, with respect to the success of the pass [98, 99], as well as the position on the field the pass was made from [100]. The tactical indicator shots on goal were evaluated against the outcome of scoring goals [101], as well as the number of passes made prior to a shot on goal [88]. The teams' ability to score goals were evaluated with respect to their passes, types of possession as well as player positions prior to scoring goals [102]. Shots on goal were also divided into three categories (shots on goal, shots on target, goals scored) and evaluated against multiple tactical indicators related to offensive (types of moves, passing, dribbling, etc.) and opponents defensive (fouls, red cards, clearing the ball, etc.) play [103].

Attempts have also been made to evaluate the game of soccer in its entirety, rather than specific points in time, through the evaluation of possession and multiple attacking and defensive tactical indicators. The tactical indicator possession was evaluated against the time [104] as well as the location on the field at which possession was maintained [105]. Possession was also divided into three categories (defensive, counterattacking,

and elaborate attack) and evaluated against the position on the field, number of passes, and the outcome of the possession [106]. The defensive play alone of a team has been evaluated through defensive tactical indicators (tackling, clearance, blocks, etc.) against team success [107]. Multiple tactical indicators related to both attacking (shots, goals, etc.) and defensive (tackles, clearance, etc.) play were also evaluated against team success [108] and individual play [109].

An interesting point of note is the use of position as a tactical indicator. In all studies that involved position [98, 100–102, 105, 106, 108], the field of play was divided to multiple cells termed "zones" (Figure 2.5). These cells were large enough for a player to move within them and perform identical actions. However, if an action (tactical indicator) was performed and annotated within a cell, it was considered identical to all other occurrences of the same action within the same cell. Hence, player movements within each tactical cell were ignored and all positions within each cell were considered equal in a tactical sense.

In most cases where the field of play was divided to tactical cells, the cells were not quantified, nor were there reasons as to why the particular cellular arrangement was chosen. It can be assumed that the cells are intuitive to the sports, and hence, the manual annotation by a domain expert would not require it being quantified.

Figure 2.5 Division of a soccer field into tactical cells. (a) Three equal lengthwise thirds [106]. A grid of nine equal zones (b) [100].

2.3.1.2 Basketball

In basketball, the tactical indicators with respect to scoring and defense have been established for many years. These tactical indicators, such as, 2 point shot attempts and 2 point shots made, 3 point shot attempts and 3 point shots made, free throw shot attempts and free throw shots made, rebounds, assists, steals, etc., have been used often. These tactical indicators have been evaluated against winning and losing in games [110–112] and individual quarters of a game [113–115]. In addition, the ability of an attacking player to attempt and make 2 and 3 point shots have been evaluated against the distance of the defensive player from the attacker [116]. The tactical indicator rebounds have been evaluated against the position on the floor the rebound is gathered at, with respect to the position on the floor which the preceding shot was attempted from [117].

The attacking and defensive possessions have also been used as a tactical indicator. The attacking possessions of a team have been analyzed against their success and failure, the action causing the success or failure, the position on the court and time of game [118]. The attacking style of possessions (fast break, early offense, set offense) have been evaluated against the action that caused the start of possession, the time of possessions, actions during possession and outcome [119]. The ability of an attacking team to score points, make passes and keep possession of the ball has been evaluated against the defensive style (man to man, zone half court and zone pressure) of the opponent during the possession [120].

The trend of dividing the field of play (court) into tactical cells have also been observed when using position as a tactical indicator in basketball [117, 118]. This is illustrated in Figure 2.6. Similar to soccer, the borders of these cells are not quantified and the sizes of the cells allow players to move within each cells.

Figure 2.6 Division of a basketball court into tactical cells [117].

2.3.1.3 Field hockey

A key situation for scoring goals in field hockey is called a penalty corner. The description of events leading to a successful or unsuccessful penalty corner has been evaluated as tactical indicators [121]. For successful penalty corners, these descriptions include, the direction of shot (straight or lifted) and the number of deflections before scoring. For unsuccessful penalty corners, the descriptions include reasons for missing a goal, such as save, hitting wide or loss of control. The routines of teams taking the penalty corner have also been considered a tactical indicator [122]. The routines were called drag-flick, move and shot, slip right, double slip right, slip left, double slip left, etc., and were evaluated against the outcome. A similar description for the routine has also been used to evaluate the difference of penalty corner strategies in male and female field hockey teams [123].

The scoring and attempted scoring arising from all situations of a field hockey match have also been evaluated [124, 125]. In these analysis, the action preceding the attacking possession, the action used to pass the ball to the goal region on the field and time taken to score were evaluated with respect to the position on the field. The location on the goal where the ball entered was also evaluated.

As was the case with soccer and basketball, the field of play has been divided into cells and positions annotated with respect to these cells [122–124] (Figure 2.7 (a)). Additionally, in field hockey, a similar representation is observed in evaluating the location on the goal where the ball entered [124, 125] (Figure 2.7 (b)). Although these cells are not quantified,

in hockey, most of the cell borders can be safely assumed from other standard lines on the field and goal. For example in Figure 2.7 (a), most of the cell lines are based on the width of the field, goal, and penalty area. In Figure 2.7 (b), the cells are divided according to the solid board on the bottom of the goal and the net region.

(a) (b)

Figure 2.7 Division of a hockey field and goal into tactical cells. (a) Hockey field [122]. (b) Hockey goal [124].

2.3.2 Racket sports

Published literature on manual tactical analysis of two popular racket sports, tennis and squash, were reviewed.

2.3.2.1 Tennis

Tennis is a game with non-continuous segments of play called rallies. The start of these rallies start with a service (first shot) by one player which is received (reply shot) by the opponent. The serving is considered an advantage in tennis and has been evaluated.

The action of serving has been evaluated as a tactical indicator with respect to winning points as well as winning consecutive points while serving [126]. Service has also been evaluated in combination with other tactical indicators, such as, speed of service, outcome

type of winning points (ace, double faults, winner, unforced error), points won close to the net, number of shots in a rally, rally time, etc., [127, 128].

Movement patterns in tennis have been divided with respect to hitting the ball as initial movement, step type during movement, movement immediately preceding the shot and recovery step [129]. These movements have been evaluated against the shot type and outcome of the shot as well as the position. For this position annotation, the tennis court was divided into tactical cells (Figure 2.8). However, these cells are not clear and are extremely difficult to understand.

Figure 2.8 Division of a tennis court into tactical cells [129].

2.3.2.2 Squash

In notation analysis of squash, the shot type (volley, boast, drive, etc.) has been used as a tactical indicator. The shot type has been evaluated against the outcome of the shot [130], as well as a combination of shot direction and outcome [131]. Position has been used as a tactical indicator in analyzing the type of shot against the position at which it was hit from [67], and a combination of the position and shot outcome [93]. Time available to play a reply shot following the opponent playing a shot was used as a tactical indicator and analyzed against the type of shot played and position at which it was played from [132].

Actions leading to a squash player losing control of the play were defined as perturbations and analyzed during squash matches [133]. These actions were, unreturnable shots and miss-hits by the opponent. These perturbations were evaluated against the shot type, and the location of the court at which they occurred.

In all studies involving position as a tactical indicator, the squash court was divided into tactical cells [67, 93, 132, 133]. Manual notational analysis have divided the court cells intuitively, while studies involving automated data gathering for subsequent manual analysis, required to quantify the cell borders. This is illustrated in Figure 2.9.

(a) (b)

Figure 2.9 Division of a squash court into tactical cells. (a) Unspecified intuitive cells [93]. (b) Optimized and quantified cells for automated data gathering [132].

2.3.2.3 Badminton

The focus of this thesis is on the sport of badminton, and hence, a thorough search of the published literature on notional analysis of badminton was conducted.

Several studies on notational analysis of badminton matches involved annotating time taken per rally in order to evaluate the characteristics in the game of badminton with respect to the shots played. This allowed evaluating the time of play (rally time) against the frequency of total shots played in the rally [134], rally and rest times against the frequency of types of shots [135], as well as rally length with respect to the progression of the match and the last shot of the rally [136]. A review of annotating the time of rallies concluded that information on rally time and the number of shots would be useful in developing a

training program, in order to allow athletes to attain levels of physical performance suited to compete in international badminton [137]. However, such information does not provide a tactical perspective on the game of badminton.

Another study for understanding badminton game characteristics evaluated the difference between points scored by the two players during different phases of a badminton match [138]. This study concluded that the winning player had a net positive point difference compared to the loser. This conclusion seems intuitive, given that badminton is decided on winning more points, and also does not provide a tactical perspective on badminton.

A study conducted to evaluate the perception of badminton coaches on using performance analysis [139] evaluated the types of shots played by badminton players with respect to the location on the badminton court they were played from. The badminton court was divided to six tactical cells (Figure 2.10 (a)). Seven types of shots were evaluated against the cell at which they were played from as well as their outcome. While this study was conducted to evaluate the perception of a coach, the tactical indicators gathered reflect similar indicators used in other sports for tactical analysis. It stands to reason that these tactical indicators could be used in the tactical analysis of badminton. Several other studies, focusing on notational tactical analysis of badminton followed a similar approach, where shot types were evaluated against six [140, 141], and eight [142] tactical cell positions. A study on doubles badminton evaluated the types of shots and the outcome without evaluating the location at which the shot was played from [143]. However, they did evaluate the first shot (service) with respect to four tactical cells at which the service was received. While the number of tactical cells and the types of shots evaluated differ from study to study, the similarities of tactical indicator types confirm this as a suitable approach for manual notional tactical analysis of badminton.

The tactical cellular space had not been quantified in any of the previous studies on badminton tactical analysis. Neither has a reason been given as to why the particular

cellular arrangements were used. Additionally, it is difficult to interpret the cell borders based on standard lines on a badminton court.

(a) (b)

Figure 2.10 Division of a badminton court into tactical cells. (a) Six cells [139]. (b) Eight cells [142].

2.3.3 Summary

In all sports, tactical indicators have been identified with respect to the sport itself or important segments of the game flow. For example, in soccer, the event of scoring goals and actions preceding the goal are focused on. In basketball, the action of shooting the ball as well as actions before and after the shot are evaluated often. Hockey focuses on penalty corners and preceding actions.

The three racket sports appear to have different tactical structures. Tactical analysis in tennis concentrated on service as the most important action of the game. The type of shot did not appear crucial, and is reasonable considering most shots played in tennis are fast flat shots either straight or across the court. Although the environments (courts) used for squash and badminton are considerably different, both sports appear similar from a tactical

perspective. Notational analysis in both sports often evaluated the type of shots and the location from which the shots were played from.

Finally, positions have been annotated with respect to zones (tactical cells) and all positions within each tactical cell are considered the same in a tactical sense.

2.4 Approaches for automated tactical analysis

The overall goal of this thesis is the development of a comprehensive automated approach for tactical analysis in badminton (Section 1.3). A detailed understanding of past work on automated tactical analysis is required, before identifying possible avenues to pursue in developing an automated approach for badminton. In this section, automated approaches that can be used for tactical analysis are reviewed, focusing on the two fundamental tasks, data gathering and data processing (analysis).

2.4.1 Automated data gathering

This section discusses the automated approaches used to gather latent information and extract tactical indicators. A brief review of studies in sports are discussed first, followed by a detail discussion on approaches used for badminton.

2.4.1.1 Automated data gathering in sports

Tactical analysis focuses on strategies (game plan) and tactical decisions of teams and individual athletes, with the intention of providing feedback to athletes in order to improve tactical performances. A coach or tactical analyst plans to limit the tactical strengths and exploit tactical weaknesses of opponents, in order to defeat the opponent. This requires gathering tactical information from opposing teams or athletes. At international elite competitions, an opposing team or athlete would not allow sensors being placed on them by another team. Therefore, automated data gathering approaches requires remote sensing, often through video capture, image processing and tracking.

This is reflected in tactical information gathering in most sports, such as soccer [38, 144], basketball [145, 146], tennis [76, 147] and squash [67, 148], where video captured at competitions have been used to identify and track players using various image processing approaches. Video footage has been extracted from broadcast video [146], captured through cameras placed on the ceiling of the competition venue [147, 148], as well as multiple cameras placed around the venue [67, 144].

2.4.1.2 Automated data gathering in badminton

When examining studies on automated data gathering in badminton, the competing environment and the rules related to international badminton tournaments must be considered. International badminton competitions are held throughout the world, and the organizing nations have the right to gain competitive advantages by implementing rules regarding camera placement. Based on feedback from the Malaysian national badminton team, each competing team is allowed to place a camera at the back of the badminton court, at an elevated angle similar to video captured for television broadcasts. This negates the use of sensors such as Kinect [149] as a potential approach for automated data gathering.

Shuttlecock tracking

Several studies on automated data gathering in badminton have concentrated on tracking the shuttlecock (ball) and extrapolating the types of shots played from these trajectories [150–152]. A study on extracting the shuttlecock trajectory from 2D seriate images using video footage captured at training environments yielded encouraging results in extrapolating the types of shots [150]. However, the camera placement in this study was at the side of the training court and is not a feasible option at international competitions. The studies using broadcast video [151, 152] divided each half of the badminton court to nine equal sized tactical cells. The shuttle trajectories were tracked with respect to these cells and the types of shots played were extrapolated. The results were substantially poor in comparison to the study at a training environment. The deficiencies of the algorithm in detecting the

shuttlecock using broadcast video had been identified by the authors as the main reason for this poor performance. This is a reasonable conclusion considering the video angle, size of the shuttlecock and the speed at which it moves.

Service event detection

Two studies have concentrated on detecting the service event in badminton [153, 154]. One of these studies have used video captured by a camera fixed to the ceiling of the competition venue [153]. Once again, this is not a realistic expectation at a competition venue. A later study using broadcast video [154] employed a technique based on image subtraction for player position detection. The configuration of the players (angle at which the player stand with respect to each other) was used in identifying the activity of serving. Unfortunately, the results of service detection was poor, and is reasonable, considering a similar player configuration is possible during the playing time of the match. A comprehensive study on video analysis [155] (detailed explanation below) also detects the service event with substantially better results. However, detecting the action of service only provides information on when the badminton rally starts. This information is not a tactical indicator and is insufficient for tactical analysis.

Player position detection and tracking

A study on automated analysis of broadcast videos from court-net based sports [155] propose a complicated algorithm for court, player position, and event detection. Similar to the previously mentioned study on service detection [154], an approach based on image subtraction is used for player position detection. The player positions are identified by subtracting a background model developed from the start of the game when the players are not present on the court. The resulting image includes the players as blobs (segments) and the player positions can be identified through these segments. The assumption is that the background does not change during the entire match, except for the player movement on court. The same study also proposes an algorithm to identify and handle occlusion.

The occlusion situations are assumed to have certain properties. First, the heads of the players do not occlude each other, and are visible as peaks in the extracted player segments. Second, the player movement direction is expected to continue unchanged from before the occlusion.

This is an interesting and comprehensive approach, and is the most promising study with respect to automated data gathering in badminton. However, most of the techniques were discussed with respect to tennis and appear to be based on assumptions made on the game of tennis. For example, an assumption is made that the players always stands at the baseline of the court before the start of a rally. This is not the case with badminton and volleyball. A closer examination of previous work by the same authors [156–160] confirmed that the studies are based on the game of tennis, and its application in other court-net sports are discussed. The deficiencies in applying this technique in badminton have been discussed by the authors [159], and the player position detection, tracking, and occlusion handling have not been evaluated for badminton.

The approach proposed is complex, comprehensive, and clearly applicable in tennis. This study provides a possible avenue in pursuing an automated data gathering approach for badminton, although the approach may be simplified based on unique conditions applicable to badminton and tactical analysis in badminton.

2.4.2 Automated data processing

Automated tactical analysis is the automated analysis of tactical indicators and their complex interactions with each other, in order to identify patterns and trends. This section discusses the automated approaches used to analyses tactical indicators. Unfortunately, the automated data gathering approaches for badminton, discussed above, do not involve tactical analysis and no published work was found on automated processing of badminton tactical indicators. Hence, the discussion is focused on the most relevant approaches used in other sports.

2.4.2.1 Temporal pattern extraction

Automated approaches for tactical analysis have extensively used time as a tactical indicator. Position and action indicators have been evaluated against time or the sequential order in which they occur. Temporal patterns have been used to evaluate player movements on a soccer field divided into tactical cells [161] and player configurations as tactical indicators of soccer teams [78]. This analysis builds on the ability of humans to identify noncontiguous patterns in sequential events, where relevant events are identified while ignoring the irrelevant events that occur in between the relevant ones. However, for such a pattern to be tactically relevant, the noncontiguous events of the sequence must not be separated by more than a threshold number of events or time. For example, in soccer, a pass made by a defensive player cannot be attributed in a sequence involving a goal being scored, if the original pass is followed by seven irrelevant passes which take one minute of game time. This threshold is highly dependent on the sport as well as the game situation, and would be difficult to define.

2.4.2.2 Clustering of spatio-temporal data

Other efforts in automated data processing for tactical analysis have concentrated on clustering of spatio-temporal data using artificial neural networks [77, 94, 162–168]. These studies are based on an idea of huge spatio-temporal databases with unknown tactical features. Large quantities of spatio-temporal information can be gathered through a multitude of sensors, resulting in huge databases with hidden tactical information to be mined. Supervised data mining approaches are not useful in these situations, as the tactical features are unknown. Artificial neural networks are useful in identifying "hidden" features in the spatio-temporal data and clustering useful (tactical) information.

Spatio-temporal data have been clustered to identify tactical movement patterns in squash [77, 167], soccer [94, 164], volleyball [163], basketball [165], and handball [166, 168]. The results discuss tactical information gathered from spatio-temporal data, such as common trajectories (tactics) used by an athlete [77] or formations used by a team

[94]. The ability of this approach to extract hidden tactical patterns from spatio-temporal data is seen as an advantage. However, this advantage of discovering hidden features is redundant in situations where the features to be extracted from spatio-temporal data is known. For example, if the typical tactical movement patterns of a squash player can be defined, supervised approaches can be used for mining these tactical patterns.

The underlying principles of clustering (unsupervised learning) provide disadvantages as well. In these approaches, the input data is clustered according to hidden features [169, 170]. Inputs with common features (tactics) are clustered together, allowing examination and interpretation of the most common tactics in a data set. However, the clusters are not defined by a user, and hence, examination and interpretation is time consuming. Additionally, if a new data set, say from a new match, is used as the input, a completely new set of clusters may arise. The clusters from the two data sets do not reflect the same tactics and does not allow meaningful comparative analysis between matches.

2.4.2.3 Classification of spatio-temporal data

The most relevant studies on data processing for tactical analysis have been conducted in the sport of tennis, where supervised classification approaches have been used to identify tactics in spatio-temporal data.

A study on archiving tennis video clips [76] used the ball trajectory as latent information. The locations of tennis service was extracted as a tactical indicator using Bayesian rules. This information was used to classify the video clips, where serving location was considered a tactic. However, the service location cannot be considered a strategy, and is instead a tactical indicator.

Another study on tennis video indexing [171], used four tactical indicators (player movements to the net, left, right, and standing still). These tactical indicators were given a symbolic representation, represented in a sequential manner and frequent sequential movements identified using the Teiresias algorithm [172]. These frequent sequential movements were considered tactics and frequency counts used to examine tactics in tennis.

Figure 2.11 Similar rallies of tennis [173].

Although the frequent sequential movements do provide a tactical understanding of each individual movement, the approach does not allow comparison of a group of movements to understand the underlying tactical structure. This is especially true if a large number of tactical indicators are used and a large number of frequent moments identified. In such a case, an appropriated data mining technique is required for further data analysis. In a sense, these frequent sequential movements can be considered tactical indicators, which can then by analyzed further to understand the underlying tactics and strategies.

A larger set latent information was used in a slightly more complicated study involving player movements, type of shots and ball speed [173, 174]. The game of tennis was described with respect to the events of a shot being played. At each event, a combined symbolic representation was provided to describe player position, ball speed, and the type of shot. Similarity measures were defined for single events, and for a sequence of events. The similarity measure allow extracting frequently repeated rallies and have been considered strategies in tennis. However, when evaluating the results of this study, the frequently repeated rallies appear to have similarities between them. For example, in Figure 2.11, the two left most rallies depict similar strategies. In a sense, the frequently repeated rallies can be considered tactical indicators, rather than tactics themselves.

Another study on tactical analysis of tennis used player speed, direction, and location on tactical cells of a tennis court as tactical indicators [175]. The combination of these tactical indicators were described as symbols. Seven typical tactical sequences were defined. The longest common subsequence was used as a similarity measure to classify spatio-temporal data as belonging to these seven tactical sequences. Defining typical tactical sequences allow classifying inputs to a set number of known groups, and therefore, allow inter match comparisons. This approach provides an avenue of pursuit for automated data processing in badminton.

2.4.3 Summary

Automated approaches for gathering latent information and extracting tactical indicators have focused on remote sensing though video capture, image processing and tracking. Studies on badminton have focused on tracking the shuttlecock, detecting service action, as well as player position detection and tracking.

Shuttlecock tracking has not provided encouraging results when using video footage captured from a view that is available at international badminton competitions. Furthermore, the events extrapolated from the shuttle trajectory have not been accurate. The detection of service activity only provides information on when the badminton rally starts, and is insufficient for tactical analysis. Player position detection and tracking based on image subtraction appears to be a promising approach to pursue.

Several methods were identified for automated spatio-temporal data processing. Temporal pattern extraction relies heavily on identifying a threshold for a maximum separation in relevant events. Unsupervised clustering provides an advantage in detecting hidden tactical features, although this is redundant in situations when features are known. The main disadvantage of clustering is that it does not allow meaningful inter match comparisons. Supervised classification approaches allow inter match comparisons and are useful where typical tactics (features) can be defined.

2.5 Conclusion

This chapter aimed to provide a perspective on badminton tactical analysis, focusing on the fundamentals of tactical analysis, manual approaches used in tactical analysis, and possible automated approaches to be used in the automation of badminton tactical analysis.

Performance analysis is a method for evidence based decision making, through the systematic gathering of performance indicators and subsequent analysis. This process is founded on the fundamentals of notational analysis where manual annotation is used to gather performance indicators. Tactical analysis is a sub category of performance analysis, where tactical indicators are gathered and analyzed to evaluate tactical performance. Tactical indicators in sport reflect the relative importance of events in the specific sport with respect to tactics. All tactical indicators can be classified to three groups representing the latent (high level) variables action, position and time. In badminton, the types of shots (action), time of shot (time), and the movement of players (position) on tactical cells of a badminton court are important tactical indicators.

Automated approaches for tactical data gathering in sports use video footage, where Latent information is gathered and tactical indicators extracted. In badminton, shuttlecock trajectories have been gathered to extract action indicators (types of shots). However, this has not been successful when using video footage with a view similar to that available at international badminton tournaments. Using an image subtraction based approach for player position detection is a potential avenue to be explored in gathering position information from badminton video. This can be linked to the first research question in Section 1.4.

- How can tactical information of badminton players be automatically gathered at international tournament environments?

Badminton position tactical indicators are represented on tactical cells of a badminton court. A variety of cellular spaces have been used in notational analysis of badminton as well as automated shuttlecock trajectory tracking. No reasons have been provided for

selecting the number of tactical cells. Only the studies on automated tracking provide a quantified measure for tactical cell borders, and once again, no reasons were provided for this. Hence, the number of optimal cells must be identified and the cellular representation quantified with reasons, before position data can be represented according to these cells and tactical indicators extracted. This can be linked to the second research question in Section 1.4.

- How can tactical indicators be extracted from the automatically gathered tactical information?

Large databases of tactical indicators require processing to identify useful tactics and strategies. Provided the typical tactical features of gathered tactical indicators (badminton movements) are known, a supervised classification approach is suitable for assigning these tactical indicators to typical tactical groups. Such a grouping allows a badminton domain expert (tactical analyst or coach) to understand their underlying tactical implications. However, it should be noted that the approach should be adaptable to unique domain constraints present in badminton tactical analysis. This can be linked to the third and fourth research questions in Section 1.4.

- Can the tactical indicators be analyzed in order to easily comprehend their underlying tactics?
- Can the analysis method easily be adapted to domain requirements in badminton tactical analysis?

The underlying tactical implications are presented to a badminton tactical analyst and subsequently a badminton coach. This type of information has traditionally been represented in numerical or tabular form. However, a visual representation allowing efficient comprehension and comparison of the underlying tactical features is advantageous. This can be linked to the fifth research question in Section 1.4.

- Can the underlying tactics and strategies be represented in a manner that allows efficient comprehension?

The subsequent chapters of this thesis aim to address these research questions.

CHAPTER 3

Automated data gathering: An image processing approach for player position detection

Automation has been a growing trend in recent times where technological agents have replaced humans in performing physical, perceptual and even cognitive tasks [176]. A prime candidate for automation are simple tasks, often considered tedious and boring for human operators. These technological systems also improve efficiency and precision of simple tasks while simultaneously allowing human operators to focus on meaningful and intellectually stimulating tasks.

Tactical analysis of sports require the menial and monotonous task of gathering tactical information prior to analysis and development of counter tactics. If this menial task of data gathering can be automated, human tactical analysts would be free to focus their time and efforts in tactical analysis. With this in mind, this chapter attempts to tackle the 1st research question presented in Section 1.4.

- How can tactical information of badminton players be automatically gathered at international tournament environments?

3.1 Introduction

Sports performance is evaluated through the analysis of quantifiable measures that define performance called performance indicators [34]. These measures quantify and describe some or all aspects of sports performance. The measures that define tactical performance are referred to as tactical indicators, and are derived from higher order latent information related to action, position and time [36]. Hence, in the simplest terms, tactics are evaluated through quantifying, what happened, where and when. The manual task of gathering latent information can be automated, allowing subsequent extraction of tactical indicators and analysis.

Automated data gathering for sports tactical analysis has revolved around computer vision approaches. This is a result of the highly competitive nature of sports, especially at the international level, where athletes would not allow sensors to be placed on them by opposing teams. Additionally, at international badminton competitions, competing teams are only allowed to record video footage from one camera, placed at the back of the court, at an elevated angle similar to video footage observed in television broadcasts of badminton (Figure 3.1). A review of approaches used for automated data gathering in badminton (Section 2.4.1.2) identified player position detection as the most appropriate avenue for exploration.

Figure 3.1 View of the badminton court as captured on video by a competing team at an international badminton tournament.

This chapter aims to develop a method to automatically gather latent player position information from video footage captured by a competing team at an international badminton tournament. An image processing approach is proposed for this task. The ability of this approach to detect player positions have been validated using video footage captured at multiple international tournaments.

3.2 Overview of work

Figure 3.2 illustrates the flow of work documented in this chapter.

Figure 3.2 Overall flow of work documented in Chapter 3.

In Section 3.3, an image processing algorithm was developed to identify the positions of badminton players on both halves of the badminton court. On some occasions, the badminton players occlude each other. An appropriate method was developed to identify and handle occlusion, allowing individual player positions to be calculated. In Section 3.4, experiments were conducted to validate the ability of the image processing algorithm to identify player positions.

3.3 Player position detection

An evaluation of approaches used for automated data gathering in badminton (Section 2.4.1.2) identified a study on automated video analysis of all court-net based sports [155] as a potential avenue for exploration of player position detection. This study proposed a complex algorithm for court, player position and event detection, based on the sport of

tennis and situations unique to tennis. This algorithm can be simplified and adapted for the problem at hand. The image processing algorithm used in this thesis differs from this study as explained below.

In the above mentioned study, the court lines were automatically identified to calibrate the image and extract the court region. However, in badminton tactical analysis, automating this process is not required. The playing region can be extracted by manually identifying the court region at the start of the match. This information can also be used to identify the real world positions of the player from the pixel coordinates, rather than calibrating the entire image of every frame.

In the same study, a background model was developed when the players were not present on court. The service situation in tennis where players are located at the baseline was used to develop this background model. This model was subtracted from each frame of the video in order to identify the player positions (motion). However, in badminton, the players do not stand at the back of the court when serving. Hence, a better approach is to use image subtraction to identify player movements.

Additionally, the three-dimensional player positions were identified in the study on tennis. However, this is not required for badminton and the two-dimensional position on the court floor is sufficient. The player position locations were identified with this in mind.

3.3.1 Materials

Video footage of badminton matches captured at international badminton tournaments by the Malaysia National Badminton team was used in developing the image processing algorithm. The video footage was obtained from the video library of the National Sports Institute of Malaysia, and were from tournaments organized by the Badminton World Federation on their Super Series Tour, the Badminton World Championships and multi-sport events such as the Olympic Games and South East Asian Games.

The native functions available in the National Instruments LabVIEW Professional Development System [177] and the Vision Development Module [178] add-on were used

to implement the image processing algorithm. Video footage was converted to avi format (resolution 720×576) using Oxelon media converter [179] (version 1.1).

3.3.2 Image processing approach

The following steps (figure 3.3) were implemented for player position detection. Native functions and operations in LabVIEW Vision and the parameters used are detailed below. Low level functions available in LabVIEW Vision were used in most steps due to convenience, except when the function impeded efficiency. For example, in image subtraction, the high level numerical operations were utilized.

Figure 3.3 Flow of image processing steps for player position detection.

1. **Court corner annotation: -** The four corners of the court were manually annotated and their pixel coordinates extracted from the first frame of video footage (Figure 3.4). This information is used to extract the court (playing) region and player position calibration in later steps.

   Function name: - IMAQ select point

Figure 3.4 Corners of a badminton court to be manually annotated on the first video frame.

2. **Convert to grayscale: -** Every third frame of the video was converted to a grayscale image (256 levels of grey) by extracting the luminance frame (Figure 3.5 (a)).

   Function name: - IMAQ ExtractSingleColorPlane

3. **Image subtraction: -** The resulting image was represented as a two-dimensional array and the difference between every third frame of the video was used to identify motion. An illustration of the resulting array converted to an image is in Figure 3.5 (b). Subtracting every third frame was chosen in order to eliminate processing lag. The processing time required for the image processing algorithm was examined. Skipping two frames was chosen as a method to allow processing videos at 30 frames per second without a lag.

   Function name: - IMAQ ImageToArray, Numerical/Subtract

4. **Court region extraction: -** Figure 3.5 (b) shows that the entire background has been masked through image subtraction. However, at certain situations, tournament officials walk at the back of the court and result in motion being detected. This motion can be removed by extracting the court region. The pixel coordinates from the court corner annotation step were used to convert all pixels outside the playing region to a gray value of zero (black).

   Function name: - Comparison/Select

5. **Convert to binary: -** All pixels with a gray value above 40 were normalized to 1 (white) and the remainder normalized to 0 (black). An illustration of this array converted to an image is in Figure 3.5 (c). This value was chosen through trial and error by examining values starting at 1 until 60.

   Function name: - Comparison/Select

6. **Morphological operations: -** The resulting two-dimensional array was converted back to an image in order to use the low level functions available in LabVIEW. Several morphological operations were used (closing with a 9×9 kernel, single 3×3 erosion and drawing the convex hull) in order to remove noise from the binary image and to combine the segments (white in color) belonging to each player (Figure 3.5 (d)).

   Function name: - IMAQ ArrayToImage, IMAQ Morphology, IMAQ ConvexHull

Figure 3.5 Image processing steps. (a) Grayscale image after luminance frame extraction. (b) Image subtraction of every third frame. (c) Conversion to binary image with grayscale thresholding. (d) Player segment extraction.

7. **Player position calculation: -** To calculate the two-dimensional position of the player (Figure 3.6), first, the center of mass of each player segment was identified. Next, the bottom most pixel of each segment which shared the same horizontal position (horizontal pixel coordinate) as the center of mass was identified. This was considered

the player position (horizontal pixel coordinate of the center of mass and the vertical pixel coordinate of the bottom most pixel sharing the same horizontal pixel coordinate).

Figure 3.6 Player position calculation.

8. **Player position calibration: -** The real world player positions must be calculated from the pixel coordinates. Pixel coordinates from the court corner annotation step can be used with the known dimensions of a standard badminton court [180] to calculate the real world positions.

   Function name: - IMAQ LearnCalibrationTemplate, IMAQ ParticleAnalysis

   Given the image coordinates $p = (u, v, w)$ corresponding to Euclidean coordinates $(u/w, v/w)$, and the real world coordinates $R = (x, y, z, 1)$, the transformation of real-world coordinates to the image plane follows the following equation [155].

$$p = MR \tag{3.1}$$

$$\begin{pmatrix} u \\ v \\ w \end{pmatrix} = \begin{pmatrix} m_{1,1} & m_{1,2} & m_{1,3} & m_{1,4} \\ m_{2,1} & m_{2,2} & m_{2,3} & m_{2,4} \\ m_{3,1} & m_{3,2} & m_{3,3} & m_{3,4} \end{pmatrix} \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix} \tag{3.2}$$

   M is a transformation matrix. If the ground plane, is placed at $z = 0$, the transformation matrix becomes the homography matrix H.

$$H = \begin{pmatrix} m_{1,1} & m_{1,2} & m_{1,4} \\ m_{2,1} & m_{2,2} & m_{2,4} \\ m_{3,1} & m_{3,2} & m_{3,4} \end{pmatrix} \tag{3.3}$$

H can be estimated from the four known points (court corners) annotated previously.

3.3.3 Occlusion handling

Occlusion occurs in situations where both players are positioned close to the net (Figure 3.8 (a)). In these situations, the image processing algorithm resulted in one combined segment for both players (Figure 3.8 (b)). The positions of each individual player was required to be identified from this combined segment.

The previously mentioned study based on tennis [155], proposed an algorithm to identify and handle occlusion in court-net based sports. This algorithm is based on two assumptions. First, the heads of the players do not occlude each other and are visible as two separate peaks in the extracted player segment. Second, the player movement direction is expected to continue unchanged from before the occlusion. The first step of the occlusion handling algorithm used the two separate peaks to separate player segments. However, when occlusion occurs in badminton, two peaks were often not visible. For example, the head of the player on the bottom half of the court in Figure 3.8 (a) is directly in front of the player on the top half of the court, and does not appear as a peak in the combined segment in Figure 3.8 (b). Hence, the algorithm used in the above study cannot be used in badminton. An approach based on the unique occlusion situation in badminton is required.

When examining the occlusion situations in badminton, it was evident that players do not move laterally together. This means, the players do not remain occluded at the net, moving from left to right or vice versa. Additionally, occlusion only takes place at the net area of the court. Hence, the perspective height of players do not change substantially while occluded. The following steps (figure 3.7) were taken to detect occlusion and identify positions of both players.

Figure 3.7 Flow of image processing steps for player position detection.

1. **Occlusion detection: -** The resulting image was scanned to identify the number of segments. If only one segment was detected, occlusion handling was required.

   Function name: - IMAQ ParticleAnalysis

2. **Combined segment separation: -** The bounding boxes of each player from the previous frame where occlusion did not take place was superimposed on the combined segment (Figure 3.8 (b)). The bounding box of the player on top was positioned so that the top of the box was on the same horizontal line as the top most pixel of the combined particle. The bounding box of the bottom player was positioned so that the bottom of the box was on the same horizontal line as the bottom most pixel of the combined segment. The parts of the combined segment falling within each bounding box were considered to be the respective player (Figure 3.8 (c)).

   Given that the occlusion only occurs at the net area of the court, the height of the bounding boxes do not induce a large error when segmenting the two players.

3. **Player position calculation: -** The player positions were calculated as explained before, using the two separated segments.

(a) (b) (c)

Figure 3.8 Occlusion handling. (a) Occlusion of two players near the net. (b) Combined segment. (c) Segment separated as belonging to individual players.

3.4 Experiments and results

The automated player position detection was validated against manual annotation by a domain expert (tactical analysts of the Malaysian national badminton team) using video footage captured at international tournaments.

3.4.1 Experimental setup

3.4.1.1 Selection of video footage

Manual annotation is tedious and in order to keep this task to a minimum, the number of video frames required for evaluation was carefully considered as follows.

Selection of tournaments and matches:

When evaluating the applicability of the automated player position detection at international tournaments, multiple international tournaments were required to be evaluated. The tournaments selected were organized by the Badminton World Federation on their Super Series Tour, the Badminton World Championships and multi-sport events such as the Olympic Games and South East Asian Games. A single match from the latter rounds of each tournament (quarter final, semifinal, or final) were chosen as they involve higher levels of competition and longer rallies. The tournament venue and the lighting conditions

within the tournament remain unchanged, and hence, it was reasoned that more than one match did not require evaluating.

Selection of video section:

Within the match the camera angle and the lighting conditions remain constant. Hence, it was reasoned that the entire match did not require evaluating. The rules of badminton requires players to change sides on the court at the end of a section of play called the set (when one player reaches 21 points). Two sets of each chosen match were considered where the two players were on either sides of the court. The video section chosen for evaluation from each match were at random rallies of the match involving the middle of the set (after one player reaches five points) and covered at least ten rallies from each match (at least five rallies per set).

3.4.1.2 Manual annotation

For manual annotation, the position of the player was considered to be the midpoint between the two furthest limbs (usually feet, but in rare occasions an arm) of the player in contact with the ground. If the player has no limbs in contact with the ground (jumping) then the position remains the same as the position of take-off (last position the limbs were in contact with the ground).

3.4.1.3 Evaluation criteria

In manual annotation as well as in the automated method, player position is identified as a pixel in the image (video frame) from which the real world position is calculated through calibration. In manual annotation, a human expert is required to select a point (pixel) on the image as described in Section 3.4.1.2. The automated method identifies player position based on the center of mass of the player segment (Section 3.3.2).

However, these two points being the same is unlikely. If the center of mass is changed due to the player leaning from side to side, the automated detection would change while

the manual annotation would not. Additionally, small variations in manual annotation may occur due to tediousness of the task as well as difficulty in annotating depth (y coordinate) due to the camera perspective. Hence, a criteria was required to identify automated detection as a match to the manual annotation. For the purpose of our experiments, a distance of less than 50 cm from the manual annotation (within a circle of radius 50 cm) was considered the requirement for a correct detection. The reasoning for this is as follows.

First the body position of a badminton player on court was examined. Badminton players moving on court stand with feet distances ranging from zero (feet appear to be touching) to over 150 cm apart. In common situations this range varies between 70 to 120 cm. In all these situations, the torso position fluctuate greatly depending on where the player leans. Due to the lack of a definition based on body position, we considered the tactical perspective in defining player position. The standard length of a badminton racket is greater than 50 cm. The outstretched arm of a badminton player holding such a racket is easily capable of reaching a circular area equal in radius to the length of the racket plus the length of his/her arm. Hence, this circular area is the same position, in that the badminton player is not required to move to reach the shuttlecock. In the most difficult of situations where the player is standing upright with feet positioned with zero separation, his/her reach would still be greater than 50 cm. Hence a circle of radius 50 cm was defined as the same location in a tactical sense.

3.4.2 Evaluation of player position detection

Tables 3.1 and 3.2 illustrate the accuracy of automated position detection at different tournaments separated according to the top and bottom halves of the court. The accuracy ranges from 93.36% to 98.87% depending on the tournament and the top or bottom half of the court. The average accuracy is 96.31% and 96.86% for the top and bottom halves of the court respectively.

Table 3.1 Accuracy of automated player position detection on top half of the court.

Tournament	Number of frames	Player on top half	
		Correctly detected	Accuracy
All England Open	183	177	96.72%
China Open	241	237	98.34%
Hong Kong Open	418	402	96.17%
India Open	533	527	98.87%
Indonesia Open	422	394	93.36%
Japan Open	232	225	96.98%
Malaysia Open	247	236	95.55%
South East Asian Games	326	316	96.93%
World Championships	580	555	95.69%
Olympic Games	259	245	94.59%
Total	**3441**	**3314**	**96.31%**

Table 3.2 Accuracy of automated player position detection on bottom half of the court.

Tournament	Number of frames	Player on bottom half	
		Correctly detected	Accuracy
All England Open	183	179	97.81%
China Open	241	235	97.51%
Hong Kong Open	418	399	95.45%
India Open	533	520	97.56%
Indonesia Open	422	409	96.92%
Japan Open	232	229	98.71%
Malaysia Open	247	236	95.55%
South East Asian Games	326	310	95.09%
World Championships	580	567	97.76%
Olympic Games	259	249	96.14%
Total	**3441**	**3333**	**96.86%**

3.4.3 Analysis of errors

The size (pixel) difference of the top and bottom halves of the badminton court caused by perspective distortion was expected to affect the accuracy of player position detection. However, the results show no substantial difference in accuracy between the top and bottom

halves. This is due to the lenient error threshold chosen for a correct detection in Section 3.4.1.3, where the error caused by perspective distortion falls within this threshold.

Figure 3.9 illustrates the difference between automated player position detection and manual annotation in the x (lateral) and y (depth) axis. The difference in the y axis is often greater than the x axis.

This is due to the perspective view available and small errors in manual annotation. The depth and width of the badminton court is represented by the height and width of the video image respectively. The orientation of the video is landscape where the width has more pixels than height. This is in contrast to the badminton court, where the depth is a longer distance than the width. Hence, the depth of the badminton court is represented by less pixels than the width, and errors in manual annotation is accentuated in the y direction more than the x direction.

Figure 3.9 Sample plot of the difference between automated player position detection and manual annotation.

3.4.4 Implications in automated tactical analysis

The purpose of automated badminton player position detection is for latent position information gathering. The latent information includes all x and y coordinates gathered

from video footage. This information is to be used in order to extract tactical indicators for automated badminton tactical analysis.

3.4.4.1 Accuracy of player position detection

An examination of error plots (Figure 3.9) indicate that the errors were not concentrated and rather intermittent. The accuracy of player position detection in Tables 3.1 and 3.2 indicates that the intermittent errors occur every few seconds (less than 4% of the frames) of the video footage. Not all latent information is used as tactical indicators, and instead, data points that describe tactical features are to be extracted from this latent information. Therefore, the intermittent errors in player position detection are unlikely to have a significant impact on tactical indicator extraction. These results confirm that the accuracy of the proposed image processing algorithm and the occlusion handling method is adequate to automate latent player position data gathering for tactical analysis in badminton.

3.4.4.2 Applicability at international tournaments

The video footages used to evaluate badminton player position detection were captured by a competing (Malaysia) team at international badminton tournaments. The video capture was performed without special permissions, and from the locations allocated to all competing teams by the host organizer. The cameras used were standard camcorders commonly available on the market. This suggests that the proposed method is applicable at international tournament environments and can be used by any competing team.

3.5 Summary

This chapter takes the first step in automating badminton tactical analysis by developing a method to gather latent tactical information. The goal was to develop an automated method

for gathering player position data from video footage captured at international badminton tournaments.

An image processing algorithm was proposed for player position detection on the two-dimensional plane of the badminton court floor. Manual annotation was suggested to identify badminton court corners. This information was used to extract the court region and calculate real world player positions from the pixel coordinates. A method was proposed to identify and handle occlusion based on unique circumstances observed when two badminton players on opposite sides of the net occlude each other.

Experiments were conducted to identify the accuracy of automated player position detection, where the results of the automated method were evaluated against a manual annotation performed by a domain expert. The automated method performed at an average accuracy of 96.31% and 96.86% on the top and bottom halves of the court respectively.

The proposed approach allows the extraction of x and y coordinate data of badminton player positions from every third frame of the video footage. The result is a large quantity of latent information. For example, in a badminton match with 15 minutes of playing time, 7500 x and y coordinate pairs would be collected (assuming the video footage was recorded using a standard camera at 25 frames per second). Extracting useful data points within the context of badminton tactical analysis (tactical indicators) is addressed in the following chapter.

CHAPTER 4

Contextual data representation: Extracting tactical indicators

Information generated through technological means often results in "too much information" which is difficult for humans to comprehend. Providing structure or context to a large quantity of collected information allows extraction of relevant information [69]. This requirement for extracting relevant information is reflected in automated tactical analysis, where tactical indicators are extracted from large quantities of latent information.

In the previous chapter, an image processing algorithm was developed to automatically gather a large quantity of latent position information from badminton video footage. A contextual representation with respect to badminton must be provided to this latent information in order to extract tactical indicators. With this in mind, this chapter attempts to tackle the 2nd research question presented in Section 1.4.

- How can tactical indicators be extracted from the automatically gathered tactical information?

4.1 Introduction

Quantifiable measures that defining athletic performance called performance indicators have been used in sports performance evaluation [34]. The performance measures that define tactical performance are called tactical indicators, and have the ability to describe core tactical features of the sport [36]. For example, in soccer, scoring a goal is a core feature and location of the player when scoring the goal can be considered a tactical indicator. Tactical indicators are derived from higher order latent information [36]. In the above example of scoring a goal, positions of all players at all times are latent information while the position related to the tactical context of scoring a goal is extracted as a tactical indicator.

Chapter 3 developed an automated method for gathering latent position information in badminton. This method identified x and y coordinate data of badminton player positions as they move on a court. Even when considering a singular player, in a singular match, the quantity of latent position data gathered is substantial. A tactical context must be provided to the x and y coordinate data in order to extract tactical indicators in badminton.

A common trend observed in providing a tactical context to position data is the representation of a playing field as a cellular space (Section 2.3). The field of play is divided into tactically important cells and position data is represented on these cells. For example, in badminton tactical analysis [139], the badminton court was divided into six tactical cells (Figure 4.1), and the tactical indicators (types of shots) were annotated with respect to the positions (cells) at which they were played from. These cells are large enough for players to move inside them. However, the movement of a player within each cell is of no tactical significance and ignored in tactical analysis. Hence, in the simplest terms, all positions within a tactical cell are considered the same position in tactical analysis.

Figure 4.1 Division of the badminton court into six tactical cells [139].

One of the deficiencies in published literature has been quantifying this cellular space (cell borders). For example, in temporal pattern analysis of soccer for the purpose of tactical analysis [161], the field of play is divided into 18 cells. Although, some of the cells borders can be safely assumed with respect to standard lines on the field of play (half way line, penalty box, etc.), all borders cannot be identified in this manner. In notational analysis of badminton, the court had been divided into six [139–141] and eight [142] tactical cell positions. However, these borders were not quantified and no reasons were provided for the cellular arrangements. It stands to reason that the position annotations on this cellular space was performed by domain experts and that regions of a playing field denoted by cellular space may be intuitive to these domain experts. However, this is not adequate for automated approaches and the cellular space must be quantified.

This chapter aims to extract badminton tactical indicators from latent position information by providing a tactical context to the latent information. The ability of this tactical context to extract tactical indicators is examined.

4.2 Overview of work

In badminton tactical analysis, each half of the badminton court is divided into tactically relevant cells. This is illustrated in Figure 4.2 (a) (the cells and the cell labels in this figure are explained in Section 4.3). Badminton tactical analysts annotate the positions of players

as they transition on this cellular space allowing extraction of tactically relevant movement information (tactical indicators). The work documented in this chapter is based on these fundamentals.

Figure 4.2 Extraction of tactically relevant data. (a) Each half of a badminton court divided to nine tactical cells and labeled. (b) Plot of player transitions.

Figure 4.3 illustrates the flow of work documented in this chapter.

Figure 4.3 Overall flow of work documented in Chapter 4.

First, in Section 4.3 the optimal number of cells on a badminton court were identified through domain expert feedback and reasoning. Next, in Section 4.4, five experiments were conducted to quantify tactically relevant cell borders (experiments 1 to 5) and to develop an automated method to annotate x and y coordinated data on this cellular space (experiments 3 to 5). Transition of a badminton player on the cellular space was visualized by plotting cell labels against transition number (Figure 4.2 (b)). At each experiment,

the transition plot of the automated method was compared against the transition plot of a manual annotation performed by a domain expert, leading to enhancement of the cell borders as well as the annotation method in subsequent experiments.

Finally, in Section 4.5 the ability of the best combination (cellular borders and the automated annotation method) to replicate the intuitive annotation of a domain expert was evaluated.

- **Experiment 1:** Simple annotation 1
- **Experiment 2:** Simple annotation 2
- **Experiment 3:** Dynamic window annotation 1
- **Experiment 4:** Dynamic window annotation 2
- **Experiment 5:** Dynamic window annotation 3

In Section 4.5.4.2, x and y coordinated data was annotated on the quantified cellular space using the developed annotation method. A symbolic structurer was proposed for badminton player trajectories and frequently repeated trajectories (tactical indicators) were extracted.

4.3 Definition of cellular space

A review of approaches used for notational analysis in badminton (Section 2.3.2.3) identified that badminton position indicators are extracted with respect to tactical cells on a badminton court. Several studies used six tactical cells [139–141] while another used eight [142]. The borders of these cells were not quantified and no reasons were provided for the cellular arrangements. Two studies on automated shuttlecock tracking in badminton [151, 152] divided each half of the badminton court into nine equal sized tactical cells. Once again, no reasons were given as to why the cellular arrangement was chosen nor the reasons for dividing cells equally. Therefore, the optimum number of tactical cells for badminton tactical analysis must be identified and quantified.

4.3.1 Number of optimal tactical cells

A review of manual notational analysis in all sports (Section 2.3) indicated that tactical cells were used because the movement within these cells was of no tactical significance. However, movements from one cell to the other were considered tactically important. This was confirmed by a domain expert in badminton (tactical analyst of the Malaysian national badminton team). The domain expert suggested using nine tactical cells for the singles game of badminton (Figure 4.2 (a)), which is the number of cells used for notational tactical analysis by the Malaysian national badminton team. The reasoning for this is explained as follows.

The center position in singles badminton is considered the neutral position where a player stations himself to react to an opponents' shot. This allows him to move the least distance in covering the entire court when attempting to react and reach the shuttlecock. This position can be considered the center cell. The player would move from this center cell to another cell in retrieving the shuttlecock, and return to the center cell. Singles badminton players expect to move to either of the four corners, the two sides, or up to the net and down to the baseline. These eight positions can be considered the other eight cells.

4.3.2 Labels of tactical cells

For the experiments in the subsequent section, the tactical cells required to be labeled. The center cell was labeled 0, the corners positive numbers and the sides, top and bottom cells negative numbers (Figure 4.2 (a)). The reasoning for this labeling is as follows.

The labels were selected to simplify visual inspection of the transition plot (Figure 4.2 (b)), allowing efficient comparison of experimental results against a transition plot of manually annotated data. As mentioned previously, the pattern of play in badminton is such that a player positions at the center cell, transitions to a positive or negative cell to retrieve the shuttlecock, and returns to the center cell. Labeling the center cell 0 allows the transition plot to illustrate transitions to positive and negative numbers from the origin

line of the vertical axis. Experiments with incorrectly quantified borders would annotate the player position to an adjacent cell (positive transitions annotated as negative and vice versa). Such incorrect annotations in the transition plot of experimental data can be easily identified when compared against the manually annotated data.

4.4 Identification of tactical cell borders

All positions within a tactical cell are considered equal in tactical analysis. Domain experts did not quantify the nine tactical cell borders for manual annotation of badminton, and instead, performed the annotation based on intuitive knowledge of the sport.

Studied on automated shuttlecock tracking [151, 152] divided each half of the badminton court into nine equal sized tactical cells. However, this equal division was rejected by the domain expert. The cell sizes were expected to be different based on the types of shots played at those locations. Especially the back court region near the baseline was expected to have smaller tactical cells in comparison to the front court. This was because, at the back of the court, the shuttlecock is retrieved above the head, with the racket pointing vertically up. In contrast, at the front court, the shuttlecock is retrieved below the height of the players' head, with the racket positioned closer to a horizontal angle. This additional reach at the front court results in larger tactical cells.

In order to provide a tactical context to badminton player position data (x and y coordinates), the tactical cell borders must be identified. Five experiments were conducted and the resulting transition plots were compared against a transition plot of manually annotated data by a domain expert (Figure 4.4).

(a)

(b)

Figure 4.4 Transition plots of manual annotation. (a) Player on the top half of a badminton court. (b) Player on the bottom half of a badminton court.

4.4.1 Simple annotation experiments

At first, experiments were performed with the assumption that if the tactical cell borders were known, the x and y coordinates could be annotated to their respective tactical cells. Two experiments were conducted where the x and y coordinates from player position detection was annotated to respective cells on a badminton court.

4.4.1.1 Experiment 1: Simple annotation 1

Figure 4.5 Borders of the nine cellular segments for experiment 1: Simple annotation 1.

The borders for experiment 1 were determined by a domain expert (tactical analyst of the Malaysian national badminton team) who carefully examined multiple badminton games and identified the point on court when a player transitions from the center position (0) to the top (-1), bottom (-3), left (-4) and the right (-2). The width of the left and right cells was 1.5 meters while the height of the top and bottom cells were 1.34 and 2.68 meters respectively (Figure 4.5).

The transition plots in Figure 4.6 indicates most transitions to negative numbered cells and only a few transitions to positive numbered cells without first transitioning to a negative cell. A visual comparison against Figure 4.4 confirms this to be dissimilar to the manual annotation.

This was due to the lack of a lengthy border from cell 0 to positive numbered cells. A transition from cell 0 to cell 1 (or any other positive numbered cell), would often marginally pass through the negative numbered cells -1 or -4. Such marginal transitions to a negative cell would be disregarded by a human analyst and was annotated by the automated method.

(a)

(b)

Figure 4.6 Transition plots of experiment 1. (a) Player on the top half of a badminton court. (b) Player on the bottom half of a badminton court.

4.4.1.2 Experiment 2: Simple annotation 2

Figure 4.7 Borders of the nine cellular segments for experiment 2: Simple annotation 2.

The borders were modified upon visual inspection of results from experiment 1. The negative numbered cells were narrowed to allow a lengthy border between the center cell and positive numbered cells (Figure 4.7).

The transition plots in Figure 4.8 indicate improved transitions to positive numbered cells, although, the total number of transitions was substantially larger when compared to manual annotation (Figure 4.4).

This was caused when a player was positioned close to the border of two cells. The x and y coordinates from automated player position detection tend to fluctuate slightly in frames due to minor movements in the players body. The automated annotation resisted this fluctuation as back and forth transitions between cells when the player is located close to the border. However, this would not be considered by a human domain expert.

(a)

(b)

Figure 4.8 Transition plots of experiment 2. (a) Player on the top half of a badminton court. (b) Player on the bottom half of a badminton court.

4.4.2 Definition of dynamic window

The outcome of the simple annotation experiments resulted in a reconsideration of the player annotation method. Cellular segments were further divided into sub cells and an effect called the dynamic window was implemented (Figure 4.9).

Figure 4.9 Nine cellular segments further divided into sub cells with an illustration of the dynamic window.

The dynamic window is of 3×3 sub cells, centered on the current sub cell on which the player is located. The player is initially annotated on the sub cell that represents the relevant x and y coordinate and therefore, the respective main cell. For the player to be assigned to another sub cell and the resulting main cell, he/she has to transition outside the dynamic window. This prevents the player position being annotated on a new main cell due to small movements at the borders of a main cell. The sub cells adjacent to the border of two main cells have a width and/or height of 50 cm resulting in the requirement of a minimum movement of 50 cm before being assigned onto a new main cell. This effect was expected to replicate the intuition of a human expert where a movement of half a meter on the court would not be registered as a transition.

4.4.3 Dynamic window annotation experiments

Three experiments were conducted where x and y coordinates from player position detection were annotated on the tactical cellular space using the dynamic window.

4.4.3.1 Experiment 3: Dynamic window annotation 1

Figure 4.10 Borders of the nine cellular segments and the sub cells for experiment 3: Dynamic window annotation 1.

Borders of the main cells followed the borders from experiment 1 (Figure 4.5) while the sub cells were divided to ensure the borders were 50 cm in width (Figure 4.10)).

The transition plots in Figure 4.11 indicate a higher number of transitions to positive cells when compared to experiment 1. This was because the implementation of the dynamic window allows transitions from cell 0 to positive numbered cells. However, there were a large number of transitions to negative numbered cells, and a visual comparison against Figure 4.4 confirms the results of this experiment to be dissimilar to the manual annotation.

(a)

(b)

Figure 4.11 Transition plots of experiment 3. (a) Player on the top half of a badminton court. (b) Player on the bottom half of a badminton court.

4.4.3.2 Experiment 4: Dynamic window annotation 2

Figure 4.12 Borders of the nine cellular segments and the sub cells for experiment 4: Dynamic window annotation 2.

The borders of the main cells followed the borders from experiment 2 (Figure 4.7) while the sub cells were divided to ensure the borders were 50 cm in width (Figure 4.12)).

On visual inspection, the transition plots in Figure 4.13 appears similar to the plots of manual annotation in Figure 4.4. However, the results indicate lesser total transitions compared to the manual annotation.

This was due to two reasons. First, the implementation of the dynamic window reduces the number of transitions from cell 0 to positive numbered cells. This is because in order for such a transition to be registered, the player must move to the second sub cell within the positive cell. Second, the negative numbered cells were only divided into three sub cells. This, when combined with the dynamic window makes it impossible for transitions from positive numbered cells to negative numbered cells to be registered.

(a)

(b)

Figure 4.13 Transition plots of experiment 4. (a) Player on the top half of a badminton court. (b) Player on the bottom half of a badminton court.

4.4.3.3 Experiment 5: Dynamic window annotation 3

Figure 4.14 Borders of the nine cellular segments and the sub cells for experiment 5: Dynamic window annotation 3.

The corner sub cells of cell 0 were assigned to the respective positive numbered cells in order to facilitate the transitions between cell 0 and the positive numbered cells. The negative numbered cells from experiment 4 were further sub divided to allow transitions from positive numbered cells to the negative numbered cells.

On visual inspection, the transition plots in Figure 4.15 and the total transition number appears similar to the plots of manual annotation in Figure 4.4.

(a)

(b)

Figure 4.15 Transition plots of experiment 5. (a) Player on the top half of a badminton court. (b) Player on the bottom half of a badminton court.

4.5 Results

The automated annotation of player positions on the cellular space of a badminton court was compared against a manual annotation by a domain expert.

4.5.1 Evaluation parameters

The number of correct (true positives), extra (false positives) and missing (false negatives) transitions that were annotated in comparison to the manual annotation were considered [181] in evaluating the automated annotation.

- **Correct annotation (TP): -** A transition annotated by the domain expert is correctly registered by the automated annotation.

- **Extra annotation (FP): -** A transition that was not annotated by the domain expert is registered by the automated annotation.
- **Missing annotation (FN): -** A transition annotated by the domain expert is not registered by the automated annotation.

Additionally, accuracy, precision and recall of the automated annotation was evaluated [181].

- **Accuracy: -** The overall ability to identify the correct transition, or the percentage of correctly identified transitions.
- **Precision: -** Percentage of correctly identified transitions in the total identified transitions.
- **Recall: -** Percentage of correctly identified transitions in comparison to the transitions identified by the manual annotation.

4.5.2 Exclusion from evaluation

In order to identify a correctly annotated transition with respect to the manual annotation, the points (frame numbers) on the video footage at which the transitions occurred must be identified. The automated annotation is linked to the video frame number at which the x and y coordinates of player position detection transitioned between tactical cells. The human domain expert watched the video and annotated the transition as accurately as possible once it was noticed. However, it is unrealistic for a human to annotate precisely at the same time as the automated annotation. Hence, the automated annotations can only be matched against manual annotations at approximately the same time on the video footage, rather than at the exact frame.

If the output of automated annotation (transition plot) was not reasonably close to the manual annotation, identification of approximate points to be compared became unreliable. This was evident when visually inspecting transition plots of three experiments. The

transition plots of experiments 1 and 3 (Figure 4.6 and 4.11) showed a large number of transitions to negative cells when compared to the manual annotation (Figure 4.4). The transition plot of experiment 2 (Figure 4.8) showed a substantially larger number of total transitions. These visual inspections confirmed the results of experiments 1, 2 and 3 to be dissimilar to manually annotated data, and hence, were not further evaluated.

4.5.3 Evaluation of results

The results of experiments 4 and 5 were evaluated against the manually annotated data in detail. The number of extra transitions (false positives) had not changed substantially between experiments (Table 4.1). The number of missed transitions (false negatives) had reduced in experiment 5 while the number of correct transitions (true positives) had increased.

These results indicate that, modifications to sub cells from experiment 4 to experiment 5 has successfully enabled transitions from cell 0 to positive numbered cells as well as positive numbered cells to negative numbered cells to be correctly registered.

Table 4.1 Comparison of automated annotation against manual annotation (correct, extra and missing transitions).

	Experiment 4		**Experiment 5**	
	Player on top half	**Player on bottom half**	**Player on top half**	**Player on bottom half**
Total	174	177	174	177
Correct (TP)	114	134	156	154
Extra (FP)	15	23	23	23
Missing (FN)	54	38	15	19

Experiment 5 showed the highest accuracy at 89.66% and 87.01% on the top and bottom halves of the court respectively (Table 4.2). The higher recall of experiment 5 is indicative of the reduction in missed transitions (higher number of transitions registered) when compared to experiment 4. The higher precision of experiment 5 indicates that registered transitions were correct (true positives).

Table 4.2 Automated annotation against manual annotation (accuracy, precision and recall).

	Experiment 4		Experiment 5	
	Player on top half	**Player on bottom half**	**Player on top half**	**Player on bottom half**
Total	174	177	174	177
Accuracy	65.52%	75.71%	89.66%	87.01%
Precisions	88.37%	85.35%	87.15%	87.01%
Recall	67.86%	77.91%	91.23%	89.02%

However, the evaluation was performed against a manual annotation performed by one tactical analyst. This was due to the lack of badminton tactical analysts. The national badminton teams of the world typically employ only one tactical analyst. Additionally, the lack of a developed domestic team competition structure meant that domestic club teams in Malaysia have not advanced to the point of employing tactical analysts. The experimental results can be accepted, provided we accept the domain expertise of the Malaysian National Badminton Team's tactical analyst.

4.5.4 Implications in automated tactical analysis

The purpose of this work was to provide a contextual structure to latent position data of badminton players. This contextual structure allows extracting badminton tactical indicators that can be used for tactical analysis.

4.5.4.1 Contextual structure for player position data

The optimal number of tactical cells for badminton tactical analysis were identified through domain expert feedback and reasoning in section 4.3. This suggests that the cellular arrangement is suitable for use in tactical analysis of international badminton matches.

The dynamic window annotation method is able to handle small fluctuations in x and y coordinates from player position detection. Based on the above results, the dynamic window annotation method combined with the court cell borders of experiment 5 is the closest method in replicating the intuitive player position annotation of a badminton domain

expert. This combined approach can be used to provide a tactical structure to badminton player position data.

4.5.4.2 Tactical indicators

A review of approaches used in automated data processing for tactical analysis (Section 2.4.2) identified a study on tennis video indexing [171]. In this study, a symbolic representation was provided to tactical indicators, and frequent sequential movements were identified using the Teiresias algorithm. While this approach was claimed to identify tactics in tennis, extracting a large number of frequent sequential movements could not be considered tactical analysis, and rather, extracting tactical indicators. A similar approach was used in this thesis for badminton tactical indicator extraction. A symbolic representation was proposed for badminton player trajectories and a string matching algorithm was identified to extract frequent trajectories.

Symbolic structure for trajectories

Trajectories of badminton players as they transition from one cell to another on the tactical cellular space can be extracted in the form of numerical strings. A string is a list of contiguous characters, and in this case, the characters represent cell labels and the sequence represent transition order. For example, the following numerical string can be considered; 1 0 -4 0 -3 0 1 0 4 -3 0.

In badminton, the play is of non-continuous segments referred to as a rally. A rally starts at the service (first shot in badminton) and lasts until the shuttlecock hits the floor. The trajectory information in between individual rallies are of no significance for tactical analysis. Hence, trajectory data in the form of numerical strings were manually separated into segments starting from the service to the end of each rally, and were of variable lengths depending on the number of transitions made by a player during each rally. Tactical indicators were to be extracted from these trajectories.

Extraction of frequent trajectories

The players move all over the court and tactics change as a rally develops. Hence, the complete trajectories of each rally are also not of tactical importance. Tactically important movements (tactical indicators) were expected to be repeated in multiple rallies. Hence, the next step was to identify trajectories that players repeat during multiple rallies.

Since trajectories were in the form of numerical strings, this task could be described as identifying common substrings [182], where common substrings are contiguous sets of elements that are common to two or more separate strings. For example, the following two strings representing two rallies can be considered;

$$A = \mathbf{1} \quad \mathbf{0} \quad \mathbf{1} \quad 4 \quad \mathbf{0} \quad \mathbf{4} \quad \mathbf{0} \quad \mathbf{3}$$

$$B = \mathbf{1} \quad \mathbf{0} \quad \mathbf{1} \quad 0 \quad 3 \quad \mathbf{0} \quad \mathbf{4} \quad \mathbf{0} \quad \mathbf{3} \quad -2$$

The substrings 1 0 1 and 0 4 0 3 are contiguous elements common to both strings A and B. Hence, they are identified as repeated trajectories between these two rallies. All common substrings of at least 3 elements in length were identified.

Note: The two common substrings (1 0 1 and 0 4 0 3) can be further divided as 1 0, 0 1, 0 4 0, 4 0 3, 0 4, 4 0, and 0 3. According to the definition of common substrings, these smaller segments of the longer common substrings are also referred to as common substrings, and are common to both strings A and B. However, such smaller substrings were not considered in our work as the trajectories represented by these were already considered under the longer common substrings. All considered common substrings were not themselves a substring to a longer common substring.

4.5.4.3 A brief discussion of badminton tactics

Frequent trajectories that can be extracted from a real badminton match needs to be examined in order to continue the work on automated badminton tactical analysis.

Video footage of a badminton match, recorded at an international badminton tournament was chosen randomly from the available video library of the National Sports Institute of Malaysia. The player positions were detected using the approach documented in Chapter 3. The resulting x and y coordinate data was annotated on the tactical cellular space of a badminton court (Figure 4.2 (a)), using the borders identified in experiment 5 (Figure 4.14) and the dynamic window annotation method (Section 4.4.2). The trajectories of a player as he transitioned on the cellular space was extracted in the form of numerical strings, and all frequently repeated trajectories during multiple rallies were identified.

Table 4.3 Example of extracted frequent trajectories and the frequency of occurrence.

No.	Frequent trajectory	Frequency
1	0 -3 4 -3 0	10
2	0 3 0 3 0	9
3	0 3 0 -2 0	8
4	1 -1 0 3 0	8
5	0 1 0 4 0	8
6	0 -2 3 -2 0	8
7	0 4 0 4 0	7
8	0 4 0 2 0	7
9	0 2 0 4 0	7
10	-4 4 -4 0 2	7

Table 4.3 illustrates ten of these frequent trajectories. The frequent trajectories themselves when examined with respect to the tactical cells on a badminton court provide tactical information. For example, the most frequent trajectory (0 -3 4 -3 0), is a move from the middle of the court (cell 0) to the left back corner (cell 4) of the court and back to the middle. Trajectories 2 and 3 are both moves from the center of the court to the right back corner (cell 3) and back to center, although the movements back do not take identical paths. It is reasonable to assume that an expert badminton player or coach would be able make tactical decisions based on this kind of tactical movement information.

The comprehension of individual frequent trajectories or a small group of frequent trajectories can be executed efficiently. However, a large collection of frequent trajectories make this task substantially difficult and time consuming. The frequent trajectories in

Table 4.3 are just ten in number, while the total number of unique frequent trajectories of a single match of badminton often exceeded 200. If multiple matches are considered in the evaluation, this number may increase to thousands. Although the tactical structure of individual frequent trajectories remain the same, the underlying tactical implications in a group of frequent trajectories cannot be understood efficiently. Hence, in the continuation of work on automated badminton tactical analysis, a method for efficient comprehension of these underlying tactical implications is required.

4.6 Summary

This chapter builds on the work reported in Chapter 3, where an image processing approach was proposed for badminton player position detection. The goal was to provide a tactical structure to x and y coordinate data of badminton player positions allowing tactical indicator extraction.

The badminton court was represented as a tactical cellular space and the number of optimal tactical cells for badminton tactical analysis were identified. Experiments were conducted to identify the borders of these cells as well as a complimentary automated annotation method capable of replicating the intuitive manual annotation of a badminton tactical analyst. The cellular space was labeled in a manner that allowed straightforward visual inspection of experimental results.

In the first experiment, the tactical cell borders were identified by a domain expert. The borders were improved upon for each subsequent experiment by evaluating the results of the previous experiment. From the third experiment onwards, the cells were further sub divided and an annotation method referred to as the dynamic window was introduced. Experiment 5 showed the most promising results when compared to the intuitive manual annotation of a badminton tactical analyst, at 89.66% and 87.01% accuracy on the top and bottom halves of the court respectively.

The trajectories of badminton players as they move on the tactical cellular space were extracted in the form of a numerical string. Frequently repeated trajectories between separate rallies in badminton (tactical indicators) were extracted through a string matching approach (common substrings). Individual frequent trajectories were capable of describing the underlying tactics in badminton.

Comprehending the underlying tactical implication of all tactical indicators from a badminton match or matches is hampered by the volume of information. The time required to examine each frequent trajectory for its individual tactics, as well as the multitude of possible combinations of frequent trajectories for their combined tactical implications is prohibitive. In the following chapter, this problem is addressed in order to enhance comprehension.

CHAPTER 5

Data analysis: Classification of tactical indicators

Experimental studies of human decision makers have shown that informed decision makers often outperform the less informed. However, an information saturation point can be reached, beyond which, higher performance cannot be expected with additional information. Data analysis is used to inspect or model a large quantity of data and discover underlying patterns that supports decision making. This requirement for data analysis is exemplified in sports tactical analysis where tactical indicators are analyzed in order to understand their underlying tactics and strategies.

In the previous chapter, a method was proposed to automatically extract badminton tactical indicators. These tactical indicators must be analyzed in order to efficiently understand their underlying tactical implications. With this in mind, this chapter attempts to tackle the 3rd research question presented in Section 1.4.

- Can the tactical indicators be analyzed in order to easily comprehend their underlying tactics?

5.1 Introduction

Machine learning [183–186] is a tool that can be used to develop a model of relationships between inputs and outputs, where that relationship is often expressed as a function. Two scenarios are possible in the development of this model [186]. First, inputs may be available and are required to be assigned to output groups which have not been identified. This is referred to as unsupervised learning (clustering). In this scenario the groups (clusters) must be established through the learning process. The input data is examined for underlying patterns and similarities, allowing similar data to be assigned to clusters. In the second scenario, a collection of output groups are known and the relationship (function) between inputs and output groups must be established. This is referred to as supervised learning (classification).

Chapter 4 developed an automated method for extracting badminton tactical indicators, which must be analyzed in order to understand their underlying tactical implications. The underlying principles of machine learning is analogous to the problem at hand, where badminton tactical indicators (inputs) require to be analyzed (grouped) based on their tactical implications. Hence, machine learning can be used to automate the data analysis step in badminton tactical analysis.

Unsupervised machine learning has been used in sports tactical analysis where spatio-temporal data (inputs) have been mapped to understand individual player movement patterns as well as team structure or formation in squash [77, 167], soccer [94, 164], volleyball [163], basketball [165], and handball [166, 168]. This approach examines the spatio-temporal features of input data and is able to group (cluster) these inputs based on their spatio-temporal similarities. Hence, unsupervised learning is an appropriate method for organizing trajectory data in a manner that can be understood when examined.

However, the underlying principle of unsupervised learning acts as a disadvantage for tactical analysis. In unsupervised learning, input data is available at the start of learning while the outputs are not [169, 170]. This means that the end user has no control of the clusters being generated and have no initial understanding of their meaning. If

unsupervised learning is used for the problem at hand, the input data set would be all the frequent trajectories of one match. Once clustered, the tactical meaning of each cluster must be examined and understood. This examination is time consuming and is not feasible in a situation with time constraints, such as a badminton tournament. Additionally, if inter-match strategies were to be compared, two data sets (two sets of frequent trajectories) must be clustered. While the format of these trajectories would not differ from one badminton match to another, the individual trajectories composing each data set would. As a result, the clusters developed through machine learning would also differ. This negates the possibility of a meaningful comparative analysis of clustered data between matches and does not allow for meaningful inter-match (inter data set) comparisons.

Supervised machine learning has also been used for tactical analysis in tennis [76, 173–175]. Spatio-temporal data (input) was first represented in a manner that is context dependent on the application considered. Next the classification to pre-defined groups (classes) have been carried out using a similarity measure (function) appropriate for this context dependent representation. Because the classes are known, classification results can be efficiently interpreted and understood by an individual familiar with the classes, allowing efficient-intra match analysis. Additionally, inter-match comparisons are possible as all classes of interest are pre-defined and kept constant for multiple input data sets.

This chapter aims to develop a method to analyze badminton tactical indicators (frequent trajectories) allowing a domain expert to comprehend their underlying tactical implications. A supervised machine learning approach is proposed to for this task and its ability to perform the analysis is evaluated against the same task performed by a domain expert.

5.2 Overview of work

Figure 5.1 illustrates the flow of work documented in this chapter.

Figure 5.1 Overall flow of work documented in Chapter 5.

First, in Section 5.3.1, an appropriate classification algorithm was identified based on the domain requirements of badminton tactical analysis. Next, in Section 5.3.2 ten tactical movement groups, which are familiar to badminton tactical analysts, were defined as classes for the classification experiments. Finally, in Section 5.3.3, three different representations were proposed for the frequent trajectories and three appropriate similarity measures for classification were identified.

In Section 5.4, three sets of experiments were conducted to evaluate the classification with each representation. First, the optimum parameters for each representation were identified. Next, the classification performances with optimal parameters were evaluated in comparison with a manual classification of a domain expert.

- **Experiment 1:** String classification
- **Experiment 2:** Multiset classification
- **Experiment 3:** Vector classification

In Section 5.4.5.2, the classified frequent trajectories were visualized with respect to the ten tactical movement groups as player tactical profiles.

5.3 Classification approach

An evaluation of approaches used for automated data processing for tactical analysis in Section 2.4.2 did not identify any studies conducted on badminton. The most relevant

study was for tennis [175], where seven typical tactical sequences were defined as classes and tactical indicators classified. A similar approach was used in this thesis for analyzing badminton tactical indicators. An appropriate classification algorithm for use in badminton tactical analysis was identified. Typical tactical movements in badminton were defined as classes for classification. Different representations were proposed for the frequent trajectories as well as appropriate similarity measures for classification.

5.3.1 Classification algorithm

A variety of classification algorithms, such as instance based [187, 188], rule based [189, 190], decision trees [191, 192], support vector machines [193, 194], have been developed for a multitude of tasks. These individual algorithms have unique characteristics and issues such as speed of learning, comprehensibility, accuracy, speed of classification, amongst others [186]. Choosing a classification algorithm is a critical step [195], where the nature of its characteristics and their effect on the application at hand must be carefully considered.

The classification algorithms can be separated as lazy learners and eager learners [196]. A characteristic of lazy learners is that they do not process the training data set until a request is made to classify an input to an output class [197]. This means the lazy learners have a superior training time (no time at all) when compared to eager learners, where training the classifier requires time. This characteristic provides a vital application specific advantage in tactical analysis. If video footage of badminton matches are recorded during a tournament, new frequent trajectories can be extracted and used to improve the tactical analysis system. If training a classifier is required based on these new frequent trajectories, the system would not be available for tactical analysis during this training time. Such delays are undesirable in the time constrained environment of international badminton tournaments.

An advantage of eager learners is that training improves computational time during classification. For lazy learners, this computational time is dependent on the quantity of

stored training data [196]. Possible avenues of improving computational time is through higher computing power or a reduction in training data. Both of these options are possible in badminton tactical analysis. A badminton team can purchase computers with high computing power. Additionally, in a tournament situation, if classification is delayed beyond tolerances, the training data can be filtered efficiently.

k Nearest Neighbor algorithm

The k Nearest Neighbor (kNN) algorithm [187] is a well-known lazy learner algorithm [198] which has shown to produce accurate results when used in a suitable domain. The underlying principle of this algorithm is that elements of a data set belonging to a class would exist in close proximity (neighborhood). The algorithm computes the similarity of an input to all the elements of the training data set and assigns the input to the single most frequent class of the elements with the highest similarity value (nearest neighbors). k is a parameter defined by the user and represents the number of neighbors.

kNN also provides an additional advantage, where it can be easily explained to a non-technical person (tactical analysts of badminton, athletes and coaches). The highest level athletes and coaches in the sporting community are typically reluctant to accept new approaches and tools without careful consideration and examination. Understating of the approaches used to automate tactical analysis would enhance acceptance.

When considering the deficiencies of the kNN algorithm [196], the main concerns are as follows.

1. Requires a large storage space to store training data, as the training data is required to be used in classification of all input instances.

2. High sensitivity to the similarity measure as the classification is dependent on this.

3. Lack of established method(s) to determine the value of k.

Fortunately, the storage space requirement is of no concern in badminton tactical analysis. Large amounts of storage is required to store video footage captured at badminton

tournaments and are readily available to the tactical analysts. Additionally, an effective similarity measure and the optimum value of k can be experimentally determined. Hence, the kNN algorithm is appropriate for badminton tactical analysis.

5.3.2 Definition of classes

The classification approach is required to group frequent trajectories in a manner that is familiar to a tactical analyst of badminton. Hence, the groups themselves (classes) must be defined in a manner that is familiar and easily understandable to these tactical analysts. Such an organization of badminton trajectory data is not available in the published literature, and hence, domain expert feedback was used for this definition.

Ten tactical movement groups were defined through discussions with a domain expert (tactical analysts of the Malaysian national badminton team), where each group represented a distinct movement on a badminton court (Figure 5.2). Four groups from the center of the court to the corners (T1 to T4), two groups along the sides of the court (T5 and T6), two groups along the top and bottom (T7 and T8) and two groups along the diagonals (T9 and T10).

Figure 5.2 Ten tactical movement groups on a badminton court.

5.3.3 Modeling and similarity measures

The kNN algorithm (Section 5.3.1) is to be used to classify frequent trajectories of badminton players (repeated movements of variable lengths) to ten tactical movement groups (Figure 5.2). For this purpose, the frequent trajectories required to be represented in a manner that allows a similarity calculation between them.

Discussions with the domain expert did not reveal a standard reason as to why a frequent trajectory was classified to a tactical movement group. While each trajectory implies sequential data, on some occasions, the domain expert focused only on the frequency of transitioning on to a particular cell. This feedback was considered for two of the representations. A third representation was based on the nine cell tactical cellular space. Well known similarity measures for each representation were identified.

5.3.3.1 String representation

The sequential nature of trajectories can be represented as strings. This is exemplified in the previously mentioned study on tennis [175], where sequential information was represented as strings and the longest common subsequence [182, 199] used as a similarity measure for classification. The symbolic structure provided when extracting tactical indicators (Section 4.5.4.2) represent the frequent trajectories as numeric strings, and the same representation can be used for classification.

If we consider two frequent trajectories represented as numerical strings N_A and N_B, the similarity measure S can be the longest common subsequence, where $LCS(N_A, N_B)$ is the longest common subsequence between N_A and N_B.

$$S = LCS(N_A, N_B) \tag{5.1}$$

5.3.3.2 Multiset representation

As explained above, on some occasions, the domain expert focused purely on the frequency of visiting tactical cells rather than the order of transitions. Sequential information where the frequency of occurrence is considered without considering the order in which they occur can be represented as a multiset [200, 201]. Similarly, the numerical sequence of a frequent trajectory can also be represented as multiset, say M, where the elements of the multiset corresponds to the elements of the sequence. For example the following can be considered; $[0, 1, 0, 2, -1, 0, 4, 0]$. The Jaccard index [202] can be used as a similarity measure.

Hence, if we consider two frequent trajectories represented as multisets M_A and M_B, the similarity measure J can be the Jaccard index, where $J(M_A, M_B)$ is the Jaccard index between M_A and M_B.

$$J = \frac{|M_A \cap M_B|}{|M_A \cup M_B|} = \frac{|M_A \cap M_B|}{|M_A| + |M_B| - |M_A \cap M_B|} \tag{5.2}$$

5.3.3.3 Vector representation

The frequent trajectories of badminton players describe movements on a tactical cellular space. The number of possible elements in these sequences are limited to the number of cells. This understanding allows to represent frequent trajectories in vector space [203] and to use cosine similarity [204] as the similarity measure.

Consider a trajectory of badminton players moving on a tactical cellular space. This trajectory can be represented as a vector V according to the cells $(C_1, C_2, ..., C_n)$, where n is the number of cells, and C_n is the number of times the trajectory intersects the nth cell. The trajectory is effectively represented by an n-dimensional vector.

$$V = (C_1, C_2, ..., C_n) \tag{5.3}$$

For the case on a badminton court with nine cells (n = 9), each trajectory was represented by a 9 dimensional vector.

$$V = (C_1, C_2, ..., C_9) \tag{5.4}$$

If we consider two frequent trajectories represented as vectors V_A and V_B, the similarity measure CS can be the cosine similarity, where $CS(V_A, V_B)$ is the cosine similarity between V_A and V_B.

$$V_A = (C_{A1}, C_{A2}, ..., C_{A9}) \tag{5.5}$$

$$V_B = (C_{B1}, C_{B2}, ..., C_{B9}) \tag{5.6}$$

$$CS(V_A, V_B) = \frac{\sum_{i=1}^{9} C_{Ai} C_{Bi}}{\sqrt{\sum_{i=1}^{9} {C_{Ai}}^2} \sqrt{\sum_{i=1}^{9} {C_{Bi}}^2}} \tag{5.7}$$

C_{Ai} and C_{Bi} are components of the two vectors V_A and V_B respectively.

5.4 Experiments and results

The frequent trajectories were classified to tactical movement groups T1 to T10 (Figure 5.2) using the kNN classification algorithm. Three classification experiments were conducted. The representations and similarity measures discussed in Section 5.3.3 were used for each experiment. The results of these experiments were compared against manual classification performed by a domain expert.

5.4.1 Experimental setup

A data set of 2038 frequent trajectories were extracted from ten international badminton matches (all frequent trajectories from the matches). The matches were chosen randomly from the available video library of the National Sports Institute of Malaysia. A mix of left and right handed players were involved in the matches while some of the players featured in more than one match. Each frequent trajectory was manually classified as belonging to a tactical movement groups T1 to T10 (Figure 5.2), or as undefined by a domain expert.

This data set was used for classification and 10-fold cross validation [205] was used to evaluate the performance of each classification experiment. The performance measures used were accuracy, precision, recall, and F-score [206].

- **Accuracy: -** The overall effectiveness of the classification.
- **Precision: -** Positive predictive value, or the percentage of automatically classified frequent trajectories that correctly belong to that class.
- **Recall: -** True positive rate, or the percentage of frequent trajectories belonging to a class that were correctly classified.
- **F-score: -** Harmonic mean of precision and recall.

5.4.2 Overview of results

The highest performance for each experiment at their respective optimum parameters is illustrated in Figure 5.3. The highest classification performance was with the vector representation at 97.79% accuracy, 97.81% precision, 97.44% recall, and 97.62% F-score.

McNemar test [207, 208] was performed in order to check the statistical differences among these three approaches. The results revealed a statistical significant difference (statistically significant improvement in results) between string classification and multiset classification, as well as multiset classification and vector classification, with p-value < 0.0001.

Figure 5.3 Performances of the classification experiments.

5.4.3 Determining the optimum parameters

The optimum value of k was determined by increasing the neighborhood for classification (value of k) from 1 until the point at which the performance drops or stabilizes. The smallest value of k with the highest performance was considered the optimum value.

- **String classification** has the highest performance of 73.55% accuracy, 75.03% precision, 70.40% recall, and 72.64% F-score with a k value of 13 (Table 5.1).

- **Multiset classification** has the highest performance of 93.38% accuracy, 93.22% precision, 92.83% recall, and 93.03% F-score with a k value of 1 (Table 5.2).
- **Vector classification** has the highest performance of 97.79% accuracy, 97.81% precision, 97.44% recall, and 97.62% F-score with a k value of 1 (Table 5.3).

Table 5.1 String classification performance for different values of k.

Value of k	Accuracy	Precision	Recall	F-score
1	59.67%	67.10%	56.75%	61.49%
3	68.11%	68.54%	65.42%	66.94%
5	70.51%	69.78%	67.15%	68.44%
7	71.98%	72.22%	68.22%	70.16%
9	72.03%	73.11%	68.65%	70.81%
11	73.16%	74.29%	69.26%	71.69%
13	73.55%	75.03%	70.40%	72.64%
15	71.34%	74.02%	66.46%	70.04%
17	71.59%	73.75%	66.09%	69.71%

Table 5.2 Multiset classification performance for different values of k.

Value of k	Accuracy	Precision	Recall	F-score
1	93.38%	93.22%	92.83%	93.03%
3	91.81%	91.93%	90.40%	91.16%
5	91.95%	92.85%	90.50%	91.66%
7	91.61%	92.39%	89.95%	91.15%
9	90.78%	91.34%	89.02%	90.17%

Table 5.3 Vector classification performance for different values of k.

Value of k	Accuracy	Precision	Recall	F-score
1	97.79%	97.81%	97.44%	97.62%
3	96.47%	96.65%	95.78%	96.21%
5	95.93%	96.46%	94.96%	95.71%
7	95.34%	95.72%	94.21%	94.96%
9	94.01%	94.56%	93.04%	93.79%

Vector and multiset classifications performed best with a k value of 1. This implies that classification based on the nearest neighbor is the optimal solution for both. However,

there is a risk of overfitting when classifying based on a single sample. Noise or mislabeled data can influence the classification resulting in high errors. At the same time, it should be noted that k=1 cannot be considered a confirmation of overfitting. If the classes have clear separations, classification based on the nearest neighbor would perform well.

If an overfit occurs, the classifier is expected to perform poorly with unseen data (new data set). The cross validation approach tests the classifier on unseen data and hence reduces the possibility of an overfit although it does not completely overcome overfitting. This is especially true for the data set at hand, which was manually classified by a single domain expert, as such data cannot be considered truly independent.

Another reason for optimal performance with k=1 could be the number of classes involved. Ten classes are available, and if more than one neighbor is used for evaluation, random classification is a possibility. For example, if an input was to be classified based on k=3, the three nearest neighbors would be identified, and the input would be classified based on these three. If the three nearest neighbors belonged to three separate classes, the classification would be random, causing poor results with k=3 or higher.

As explained previously, string classification performed significantly below the other two classifications at their optimum parameters. The vector classification was the best amongst all three and performed significantly better than the next best, multiset classification. Both vector and multiset classifications performed better than the string classification, even with higher values of k where the possibility of overfitting is reduced.

5.4.4 Per-class assignment using optimum parameters

The performance of the per-class assignment to individual classes (groups T1 to T10 and undefined) were examined at optimum values of k as determined previously.

- **String classification** has a per-class accuracy of above 91%, with T9 the lowest at 91.36%. The other performance measures for the grouping varies substantially between groups, with groups T7 having a high precision at 92.23% and groups T1, T9 and T10 having a high recall at 100%, 95.61% and 93.38% respectively. The

performance is the lowest for the undefined group where the precision, recall, and F-score are 41.86%, 14.75%, and 21.82% respectively (Table 5.4).

- **Multiset classification** has a per-class accuracy above 97%, with T6 the lowest at 97.45%. The other performance measures for the classification to individual classes T1 to T10 vary, with the lowest precision (89.51%) for group T10, and the lowest recall (91%) and F-score (91%) for group T6. The lowest performance is for the undefined class where the precision, recall, and F-score are 86.67%, 74.59%, and 80.18% respectively (Table 5.5).

- **Vector classification** has a per-class accuracy above 99% for groups T1 to T10, with the exception being the undefined group at 98.87%. The other performance measures for the classification to individual classes T1 to T10 are also high, with the lowest precision (95.59%) for group T5, and the lowest recall (96.69%) and F-score (96.69%) for group T10. The lowest performance is for the undefined class where the precision, recall, and F-score are 93.81%, 86.89%, and 90.21% respectively (Table 5.6).

Table 5.4 Per-class assignment of string classification when k=13.

Class label	Accuracy	Precision	Recall	F-score
T1	97.40%	87.78%	100.00%	93.49%
T2	96.27%	80.68%	77.17%	78.89%
T3	96.81%	85.71%	82.86%	84.26%
T4	97.64%	89.47%	54.84%	68.00%
T5	95.04%	73.89%	75.76%	74.81%
T6	91.95%	69.59%	76.82%	73.03%
T7	95.68%	92.23%	54.29%	68.35%
T8	94.80%	77.84%	65.33%	71.04%
T9	91.36%	56.77%	95.61%	71.24%
T10	96.47%	69.46%	93.38%	79.66%
Undefined	93.67%	41.86%	14.75%	21.82%

Table 5.5 Per-class assignment of multiset classification when k=1.

Class label	Accuracy	Precision	Recall	F-score
T1	99.46%	95.41%	100.00%	97.65%
T2	99.51%	97.28%	97.28%	97.28%
T3	99.26%	95.77%	97.14%	96.45%
T4	99.31%	93.41%	91.40%	92.39%
T5	98.72%	93.43%	93.43%	93.43%
T6	97.45%	91.00%	91.00%	91.00%
T7	99.26%	97.06%	94.29%	95.65%
T8	98.97%	94.95%	94.47%	94.71%
T9	98.14%	90.95%	92.54%	91.74%
T10	98.87%	89.51%	96.03%	92.65%
Undefined	97.79%	86.67%	74.59%	80.18%

Table 5.6 Per-class assignment of vector classification when k=1.

Class label	Accuracy	Precision	Recall	F-score
T1	99.90%	98.95%	100.00%	99.47%
T2	99.95%	99.46%	100.00%	99.73%
T3	99.85%	99.05%	99.52%	99.29%
T4	99.95%	100.00%	98.92%	99.46%
T5	99.41%	95.59%	98.48%	97.01%
T6	99.36%	96.94%	98.62%	97.77%
T7	99.85%	100.00%	98.29%	99.14%
T8	99.61%	98.48%	97.49%	97.98%
T9	99.31%	96.93%	96.93%	96.93%
T10	99.51%	96.69%	96.69%	96.69%
Undefined	98.87%	93.81%	86.89%	90.21%

The lowest performance was observed with the undefined group for all three classifications. This is expected as frequent trajectories in this class did not show underlying tactical similarities, and instead, were trajectories that did not belong to any other class.

A recall of 100% was observed with class T1 for all three classifications, as well as class T2 in vector classification. This implies that all inputs belonging to these classes were identified correctly (no false negatives). 100% precision was observed for class T7 in vector classification. This implies that all inputs classified to class T7, belonged to that class (no false positives). These results support the discussion in the previous section

of a possible overfit, a lack of independence in the manually classified data, or a clear separations of classes.

5.4.5 Implications in automated tactical analysis

The purpose of these classification experiments were to identify a method suitable to evaluate the underlying tactical implications of badminton frequent trajectories.

5.4.5.1 Use of classification for tactical indicator analysis

Vector classification performed the best of the three classification experiments. The best results were achieved with k=1, and suggests a possible overfit, a lack of independence in the manually classified data, or a clear separations of classes. However, vector classification with higher values of k, where the possibility of overfitting was reduced, performed better than multiset and string classification.

The results indicate that vector classification with a higher value of k is the safer option to use in classifying badminton frequent trajectories. This approach can be accepted, provided we accept the domain expertise and hence, the manually classified data set, of the Malaysian National Badminton Team's tactical analyst.

5.4.5.2 Frequent trajectory visualization

The classification of frequent trajectories to ten tactical movement groups allow visualization of frequent trajectories and comprehension of underlying tactical implications. For example, Figure 5.4 illustrates classified frequent trajectories of a badminton player. A total of 307 frequent trajectories were classified to tactical movement groups (Figure 5.4 (b)) and visualized as a bar graph (Figure 5.4 (a)).

Figure 5.4 Visualization of classified frequent trajectories as a bar graph. (a) Classified frequent trajectories in graphical form. (b) Tactical movement groups from Figure 5.2.

Note: The visualization reflects tactics of the opponent. A badminton player moves to a location on court and hits the shuttlecock to a region of the opponents half of the court, which makes the opponent move. Hence, the tactics employed by a player is reflected in the opponents' movement.

The visualization illustrates tactical preferences of this players' opponent. Most notably a preference in using tactics T3 and T4, which move the player to the left and right back corners of the court (cells 3 and 4). Additionally, tactics T1, T3, and T9 (which move the player to cells 1, 3 and on the diagonal between cells 1 and 3), have been used more often than their opposites, T2, T4 and T10 (which moves the player to cells 2, 4 and on the diagonal between cells 2 and 4). Finally, tactics T5, T6, T7 and T8 have not been favored.

Such information on a players' tactical preferences would allow anticipation in future encounters as well as development of counter tactics. Hence, the visualization in Figure 5.4 (a) can be considered a tactical profile. A detailed discussion on tactical profiles is provided in Chapter 7.

5.4.5.3 Shortcomings of classification

An attempt was made to generate a new data set in order to test vector classification with new unseen data. However, this request was received poorly by the domain expert due to the tediousness of the task. This discussion revealed a shortcoming of using classification for automated tactical data analysis in badminton.

Training a classifier requires training data [209, 210]. If a badminton coach required a different tactical perspective with different tactical movement groups (classes), new training data must be manually generated by tactical analysts. This tedious manual task would not be popular with domain experts.

Additionally, this defeats the purpose of automation, where the goal is to enhance efficiency of tactical analysis. Requiring domain experts to curate training data replaces the tedious manual task of manual annotation and analysis with a new tedious task of curating training data. This may result in the automated approach not being accepted by domain experts, who may choose to continue with the familiar tedious task, rather than adapt to a new task.

5.5 Summary

This chapter builds on the work reported in Chapter 4, where badminton player positions were automatically annotated on a tactical cellular space and frequent trajectories of badminton players (tactical indicators) were extracted. The goal was to develop an automated method to analyze the frequent trajectories in order to understand their underlying tactical implications.

A method based on supervised machine learning was proposed for this task. First, a classification algorithm (kNN) with characteristics (lazy learner) best suited for badminton tactical analysis was identified. Next, ten classes (tactical movement groups) were defined through discussions with domain experts, where the domain experts were familiar with these groups and their tactical implications. Finally, three representations (strings, multisets

and vectors) were proposed for the frequent trajectories and three similarity measures (equations 5.1, 5.2 and 5.7) were identified for classification.

Three sets of experiments were conducted to evaluate classification, where results of automated classification were compared against manual classification by a domain expert. Vector classification achieved the best results, at 97.79% accuracy, 97.81% precision, 97.44% recall, and 97.62% F-score. These results were achieved with k=1, and suggests a possible overfit, a lack of independence in the manually classified data, or a clear separations of classes. However, adequate performances with higher values of k suggests that vector classification is a safe option to use in classifying badminton frequent trajectories.

The frequent trajectories of a badminton player were classified and visualized as a bar graph. This visualization allows to understand the underlying tactical implications of the classified frequent trajectories.

Efforts have been made to ensure the versatility of the proposed approach with respect to badminton tactical analysis. However, one underlying principle of classification has the potential of causing the proposed approach to be ineffective. The training of a classifier requires training data [209, 210], where in the problem at hand, that requires frequent trajectories with known class labels. In badminton tactical analysis, a coach or athlete may require the classes (tactical movement groups) to be modified in order to acquire a different tactical perspective. In such a case, the class labels change and new training data must be prepared. Preparation of this training data is tedious, often taking days, depending on the volume of frequent trajectories. A comparable approach that is not reliant on training data would negate this problem and is addressed in the following chapter.

CHAPTER 6

Applicability and adaptability in the domain: Approach to eliminate the reliance on training data

Human users adopt technologies that are beneficial and can adapt to domain requirements [211]. The use of technological agents enhance efficiency and precision in performing tedious and manual tasks. While this is seen as a clear benefit, the need to learn and use multiple technological agents in the same environment is not ideal. This is the same in sports tactical analysis, where a technological agent that does not adapt may not be adopted by the coaches and sports scientists.

In the previous chapter, a classification approach was proposed to analyze badminton tactical indicators. This approach must efficiently adapt to the requirements of sports scientists and badminton coaches. With this in mind, this chapter attempts to tackle the 4th research question presented in Section 1.4.

- Can the analysis method easily be adapted to domain requirements in badminton tactical analysis?

6.1 Introduction

The approach developed in Chapter 5 to analyze tactical indicators was a supervised learning approach. A classification algorithm was used to assign badminton frequent trajectories to ten tactical movement groups (class labels). Efforts were made to ensure adaptability of the approach at badminton tournaments. For example, the classification algorithm (kNN) was chosen to be applicable in the time constrained environment of a badminton tournament. Additionally, tactical movement groups were defined through discussions with a domain expert (tactical analysts of the Malaysian national badminton team), where each group represented a distinct movement which the domain experts were familiar with.

However, training data is required to train a classifier [209, 210]. This underlying principle prevents classification approaches from adapting efficiently at badminton tournament environments. In the problem at hand, a training data set of frequent trajectories with known class labels are required for training a classifier. During badminton tournaments, coaches may require a different tactical perspective based on tactical movements other than those represented by the tactical movement groups. In such cases, the tactical movement groups must be modified and a new training data set generated. Preparation of training data is tedious, often requiring days, depending on the volume of frequent trajectories. Hence, preparing a new training data set in the time constrained environment of a badminton competition would not be feasible.

Additionally, an automated approach for tactical analysis that introduces a new tedious manual task to be performed by domain experts becomes redundant. The domain experts may prefer to continue with the manual tactical analysis, rather than learn a new and equally tedious manual task. Therefore, an automated approach for badminton tactical analysis where domain experts are required to repetitively prepare training data, even in non-competition environments, would not be popular. A comparable approach that is not reliant on training data would negate this problem.

This chapter aims to develop a method to enhance the classification approach developed in Chapter 5 in order to eliminate the reliance on training data. A grouping approach is proposed where the frequent trajectories of badminton players were assigned to tactical movement groups based on their similarity to a representative trajectory for each group. The ability of this approach to replicate the classification approach is evaluated.

6.2 Overview of work

Figure 6.1 illustrates the flow of work documented in this chapter.

Figure 6.1 Overall flow of work documented in Chapter 6.

Section 6.3 proposes a grouping approach to assign badminton frequent trajectories to the tactical movement groups defined in Chapter 5. First, in Section 6.3.2, ten trajectories that represent the ten tactical movement groups were defined. In Section 6.3.3, the representation used for frequent trajectories in Chapter 5 were maintained, and three similarity measure were defined taking the characteristics of representative trajectories into consideration. The frequent trajectories are grouped based on their similarity with the respective representative trajectories.

In Section 6.4, three sets of experiments were conducted to evaluate grouping with each representation. First, the optimum parameters for each representation were identified. Next, the grouping performances with optimal parameters were evaluated in comparison with a manual classification of a domain expert, which was also used to evaluate classification in Chapter 5.

- **Experiment 1:** Vector grouping
- **Experiment 2:** Multiset grouping

- **Experiment 3:** String grouping

Finally, in Section 6.4.5, results of the grouping experiments were compared against the classification results from Section 5.4.

6.3 Grouping approach

The classification approach developed in Chapter 5 was required to assign badminton tactical indicators to tactical movement groups. Although this approach performed at an acceptable level for tactical analysis, the requirement of training data was identified as a deficiency in adaptability at badminton tournament environments. A grouping approach was proposed to negate this requirement for training data and replace the classification step in automated badminton tactical analysis.

The grouping approach was developed based on the underlying principles of kNN classification (Section 5.3.1) where the inputs are classified based on their similarity with each class. Badminton tactical indicators (frequent trajectories) were required to be assigned to the same tactical movement groups as in the previous chapter. The grouping approach defines trajectories representing each of these groups, and attempts to assign the frequent trajectories to groups based on their similarity with the representative trajectories. The representations for frequent trajectories from the previous chapter were maintained while the similarity measures were modified based on characteristics of the representative trajectories.

6.3.1 Tactical movement groups

The ten tactical movement groups defined in Section 5.3.2 were used for grouping. Each of these groups represented a distinct movement on a badminton court (Figure 6.2). Four groups from the center of the court to the corners (T1 to T4), two groups along the sides of the court (T5 and T6), two groups along the top and bottom (T7 and T8) and two groups along the diagonals (T9 and T10).

Figure 6.2 Tactical movement groups on a badminton court from figure 5.2.

6.3.2 Definition of representative trajectories

Ten trajectories (R_{T1} to R_{T10}) were defined to represent each tactical movement group (Table 6.1). Each trajectory represents a cyclic movement along the cells denoted by the respective tactical movement group, and the cells adjacent to at least two of the denoted cells. For example, T1 is a movement to cell 1 starting and ending at cell 0. Hence, the representative trajectory starts at 0, moves to 1 and back to 0, while passing through the two cells adjacent to cells 0 and 1, which are -1 and -4. This results in the string, 0 -1 1 -4 0. A cyclic movement on these cells include the reverse movement, 0 -4 1 -1 0. The representative trajectory R_{T1} is the combination of these two strings, resulting in, 0 -1 1 -4 0 -4 1 -1 0.

Table 6.1 Representative trajectories. Note: The illustrated representative trajectories are one cycle of the movements.

Tactical movement group	Representative trajectory name	Representative trajectory
T1	R_{T1}	0 -1 1 -4 0 -4 1 -1 0
T2	R_{T2}	0 -1 2 -2 0 -2 2 -1 0
T3	R_{T3}	0 -2 3 -3 0 -3 3 -2 0
T4	R_{T4}	0 -3 4 -4 0 -4 4 -3 0
T5	R_{T5}	0 -1 1 -4 4 -3 0 -3 4 -4 1 -1 0
T6	R_{T6}	0 -1 2 -2 3 -3 0 -3 3 -2 2 -1 0
T7	R_{T7}	0 -4 1 -1 2 -2 0 -2 2 -1 1 -4 0
T8	R_{T8}	0 -4 4 -3 3 -2 0 -2 3 -3 4 -4 0
T9	R_{T9}	0 -1 1 -4 0 -2 3 -3 0 -3 3 -2 0 -4 1 -1 0
T10	R_{T10}	0 -1 2 -2 0 -4 4 -3 0 -3 4 -4 0 -2 2 -1 0

6.3.3 Similarity measures for grouping

The frequent trajectories were to be assigned to ten tactical movement groups (Figure 6.2) according to their similarity with the representative trajectories (Table 6.1). The proposed similarity measures for grouping were based on the representations and similarity measures used for classification (Section 5.3.3). The same representations (strings, multisets, vectors) were maintained while the similarity measures were modified based on characteristics of the representative trajectories.

Note: The representations of the frequent trajectories and the similarity measures in this chapter are presented in reverse order when compared to classification (Chapter 5). This is because in Chapter 5, the results steadily improved with each representation. Hence, the most successful representation of vectors is addressed first, followed by the multiset and string representations.

6.3.3.1 Vector representation

Consider a trajectory V, in cellular space, where V is represented according to the cells $(C_1, C_2, ..., C_n)$, and n is the number of cells, and C_n is the number of times the trajectory intersects the nth cell. The trajectory is effectively represented by an n-dimensional vector.

$$V = (C_1, C_2, ..., C_n) \tag{6.1}$$

For the case on a badminton court with nine cells (n = 9), the trajectories can be represented by a 9 dimensional vector.

$$V = (C_1, C_2, ..., C_9) \tag{6.2}$$

Let V_F be the frequent trajectory and $V(R_{Tk})$ be the representative trajectory of tactical movement group Tk, where $k = (1, 2, ..., t)$ and t is the number of tactical groups.

$$V_F = (C_{F1}, C_{F2}, ..., C_{F9}) \tag{6.3}$$

$$V(R_{Tk}) = (C_{Rk1}, C_{Rk2}, ..., C_{Rk9}) \tag{6.4}$$

Vector space similarity rule 1:

A rule can be developed to group frequent trajectories based on the cosine similarity (CS) [204]. Let the similarity measure cs_k be the cosine similarity between V_F and $V(R_{Tk})$.

$$cs_k = \frac{\sum_{i=1}^{9} C_{Fi} C_{Rki}}{\sqrt{\sum_{i=1}^{9} {C_{Fi}}^2} \sqrt{\sum_{i=1}^{9} {C_{Rki}}^2}} \tag{6.5}$$

Similarity array $CSA1$ is an array of all similarity values between V_F and the representative trajectories. The frequent trajectory (V_F) is assigned to the tactical movement group corresponding to the largest element of $CSA1$. If multiple elements of $CSA1$ are highest, the frequent trajectory (V_F) is undefined.

$$CSA1 = \{cs_k\} \tag{6.6}$$

6.3.3.2 Multiset representation

A frequent trajectory can be represented as a multiset [200, 201], say M_F. For example the following can be considered; $[0,1,0,2,-1,0,4,0]$. Let $M(R_{Tk})$ be the representative trajectory of tactical movement group Tk, where $k = (1,2,...,t)$ and t is the number of tactical movement groups.

Multiset similarity rule 1:

A rule can be developed to group frequent trajectories based on the Jaccard index (J) [202]. Let the similarity measure $j1_k$ be the Jaccard index between M_F and $M(R_{Tk})$.

$$j1_k = \frac{|M_F \cap M(R_{Tk})|}{|M_F \cup M(R_{Tk})|} = \frac{|M_F \cap M(R_{Tk})|}{|M_F| + |M(R_{Tk})| - |M_F \cap M(R_{Tk})|} \tag{6.7}$$

Similarity array $J1$ is an array of all similarity values between M_F and the representative trajectories. The frequent trajectory (M_F) is assigned to the tactical movement group corresponding to the largest element of $J1$. If multiple elements of $J1$ are highest, the frequent trajectory (M_F) is undefined.

$$J1 = \{j1_k\} \tag{6.8}$$

Multiset similarity rule 2:

The representative trajectories are of different lengths, resulting in different sizes (cardinalities) of multisets ($|M(R_{Tk})|$), where some are composed of a combination of two others. For example, $M(R_{T5})$ is a combination of $M(R_{T1})$ and $M(R_{T4})$, and as a result, $|M(R_{T5})| > |M(R_{T1})|$. Due to the substantial difference between lengths of representative trajectories ($|M(R_{T5})|$ and $|M(R_{T1})|$), a frequent trajectory falling marginally outside tactical movement group $T1$ and completely belonging to group $T5$ ($M_F \subseteq M(R_{T5})$) may

have a marginally larger $j1_1$ than $j1_5$. Hence, the situation of a frequent trajectory falling marginally outside a specific tactical movement group and completely belonging to another group needs to be considered.

A frequent trajectory completely belonging to a tactical movement group Tk, would be a subset of $M(R_{Tk})$, i.e. $M_F \subseteq M(R_{Tk})$, and as such, $|M_F \cap M(R_{Tk})| = |M_F|$. To address the above mentioned situation, a rule can be established based on the cardinality of the union between M_F and $M(R_{Tk})$. First, a binary array U of elements u_k is defined, where u_i is based on the cardinality of the union between M_F and $M(R_{Tk})$.

$$U = \{u_k\} \tag{6.9}$$

$$u_k = \begin{cases} 1, & \text{if } |M_F \cap M(R_{Tk})| = |M_F| \\ 0, & \text{otherwise} \end{cases} \tag{6.10}$$

The similarity value $j2_k$ is defined based on $|M_F \cap M(R_{Tk})|$, $|M_F|$, $j1_k$ and the maximum value of array U, as follows.

$$j2_k = \begin{cases} 0, & \text{if } |M_F \cap M(R_{Tk})| < |M_F| \text{ and } max(U) == 1 \\ j1_k, & \text{otherwise} \end{cases} \tag{6.11}$$

Similarity array $J2$ is an array of all similarity values between M_F and the representative trajectories, modified as defined above. The frequent trajectory (M_F) is assigned to the tactical movement group corresponding to the largest element of $J2$. If multiple elements of $J2$ are highest, the frequent trajectory (M_F) is undefined.

$$J2 = \{j2_k\} \tag{6.12}$$

6.3.3.3 String representation

A frequent trajectory can be represented as a strings, say N_F. Let $N(R_{Tk})$ be the representative trajectory of tactical movement group Tk, where $k = (1, 2, ..., t)$ and t is the number of tactical movement groups.

String similarity rule 1:

A rule can be developed to group frequent trajectories based on the longest common subsequence (LCS) [182, 199]. Let the similarity measure, $s1_k$ be based on the LCS, where LCS_k is the longest common subsequence between N_F and $N(R_{Tk})$.

$$s1_k = LCS_k \tag{6.13}$$

Similarity array $S1$ is an array of all similarity values between N_F and the representative trajectories. The frequent trajectory (N_F) is assigned to the tactical movement group corresponding to the largest element of $S1$. If multiple elements of $S1$ are highest, the frequent trajectory (N_F) is undefined.

$$S1 = \{s1_k\} \tag{6.14}$$

String similarity rule 2:

Some representative trajectories are a combination of two others. For example, $N(R_{T5})$ is a combination of $N(R_{T1})$ and $N(R_{T4})$. However, the LCS does not take into consideration the non-matching portions of two strings. As a result, a trajectory belonging to group $T1$ would have an identical LCS_1 and LCS_5. To address this situation, a rule can be developed based on the lengths of the two strings involved in the similarity calculation.

Let the length of the frequent trajectory N_F be $L(N_F)$ and the length of the representative trajectory $N(R_{Tk})$ be $L(R_{Tk})$. The similarity measure $s2_k$ takes the non-matching portions of the strings into consideration, and is analogous to the Jaccard index [202].

$$s2_k = \frac{LCS_k}{[L(N_F) - LCS_k] + [L(R_{Tk}) - LCS_k] + LCS_k} \tag{6.15}$$

$$s2_k = \frac{LCS_k}{L(N_F) + L(R_{Tk}) - LCS_k} \tag{6.16}$$

Similarity array $S2$ is an array of all similarity values between N_F and the representative trajectories. The frequent trajectory (N_F) is assigned to the tactical movement group corresponding to the largest element of $S2$. If multiple elements of $S2$ are highest, the frequent trajectory (N_F) is undefined.

$$S2 = \{s2_k\} \tag{6.17}$$

String similarity rule 3:

The similarity measure $s2_k$ is based on the lengths of the two strings involved. However, the representative trajectories are of different lengths, where some are longer than the others. For example, R_{T5} is a combination of R_{T1} and R_{T4}. Hence, $L(R_{T1})$ and $L(R_{T4})$ are substantially small than $L(R_{T5})$. As a result, a trajectory falling marginally outside tactical movement group $T1$ and completely belonging to group $T5$ ($LCS_5 = L(N_F)$), may have a marginally smaller LCS_1 than LCS_5, but a larger $s2_1$. Hence, the situation of a frequent trajectory falling marginally outside a specific tactical movement group and completely belonging to another group needs to be considered.

A frequent trajectory belonging completely to a tactical movement group Tk, would have a length identical to the longest common subsequence, i.e. $L(N_F) = LCS_k$. A trajectory falling marginally outside a tactical movement group would have a longer length than the longest common subsequence, i.e. $L(N_F) > LCS_k$. To address the above mentioned situation, the similarity measure $s3_k$ is defined based on $L(N_F)$, LCS_k, $s2_k$ and the maximum value of array $S1$.

$$s3_k = \begin{cases} 0, & \text{if } LCS_k < L(N_F) \text{ and } max(S1) == L(N_F) \\ s2_k, & \text{otherwise} \end{cases} \tag{6.18}$$

Similarity array $S3$ is an array of all similarity values between N_F and the representative trajectories, modified as defined above. The frequent trajectory (N_F) is assigned to the tactical movement group corresponding to the largest element of $S3$. If multiple elements of $S3$ are highest, the frequent trajectory (N_F) is undefined.

$$S3 = \{s3_k\} \tag{6.19}$$

6.4 Experiments and results

The frequent trajectories were grouped to tactical movement groups T1 to T10 (Figure 6.2) according to their similarity with the representative trajectories (Table 6.1). Three grouping experiments were conducted. The representations and similarity measures discussed in Section 6.3.3 were used for each experiment. The results of these experiments were compared against manual classification by a domain expert.

6.4.1 Experimental setup

In Section 5.4.1, a data set of 2038 frequent trajectories were extracted from ten international badminton matches and manually classified to the ten tactical movement groups by a domain expert. This data set was used for the classification experiments in Chapter 5. The same data set was used for grouping experiments in this chapter.

The frequent trajectories from this data set were grouped to ten tactical movement groups (Figure 6.2). Performance of the automated grouping was compared against the domain expert classification. The performance measures used were accuracy, precision, recall, and F-score [206].

- **Accuracy: -** The overall effectiveness of the grouping.

- **Precision: -** Positive predictive value, or the percentage of automatically grouped frequent trajectories that correctly belong to that group.
- **Recall: -** True positive rate, or the percentage of frequent trajectories belonging to a group that were correctly grouped.
- **F-score: -** Harmonic mean of precision and recall.

6.4.2 Overview of results

The highest performance for each experiment at their respective optimum parameters is illustrated in Figure 6.3. The highest grouping performance was with the string representation at 97.11% accuracy, 96.96% precision, 96.95% recall, and 96.96% F-score.

McNemar test [207, 208] was performed in order to check the statistical differences among these three approaches. The results revealed a statistical significant difference (statistically significant improvement in results) between vector grouping and multiset grouping (p-value < 0.0001), as well as multiset grouping and string grouping (p-value = 0.001).

Figure 6.3 Performances of the grouping experiments.

Note: The representations of frequent trajectories in these experiments are in reverse order, when compared to classification (Chapter 5). This is because in Chapter 5, the results steadily improved with each representation. Hence, the most successful representation of vectors is addressed first, followed by the multiset and string representations.

6.4.3 Determining the optimum parameters

The representative trajectories illustrated in Table 6.1 are one cyclic movement along the cells denoted by groups T1 to T10, and the cells adjacent to at least two of the denoted cells. We aimed to determine the optimum number of cyclic movements to be used for grouping.

Similar to the experiments to determine the optimum value of k (Section 5.4.3), the number of cyclic movements were increased from 1 until the point at which the performance drops or stabilizes. The smallest number of cyclic movements with the highest performance was expected to be the optimum number of cycles.

- **Vector grouping** performs equally with one or multiple cycles of the representative trajectories at 70.76% accuracy, 77.05% precision, 72.21% recall, and 74.55% F-score (Table 6.2).

- **Multiset grouping** has the highest performance of 96.32% accuracy, 95.93% precision, 95.76% recall, and 95.85% F-score with five or more cycles of the representative trajectories (Table 6.3).

- **String grouping** has the highest performance of 97.11% accuracy, 96.96% precision, 96.95% recall, and 96.96% F-score with three or more cycles of the representative trajectories (Table 6.4).

Table 6.2 Vector grouping performance for multiple cycles of representative trajectories.

Number of cycles	Accuracy	Precision	Recall	F-score
1	70.76%	77.05%	72.21%	74.55%
2	70.76%	77.05%	72.21%	74.55%
3	70.76%	77.05%	72.21%	74.55%
4	70.76%	77.05%	72.21%	74.55%
5	70.76%	77.05%	72.21%	74.55%

Table 6.3 Muliset grouping performance for multiple cycles of representative trajectories.

Number of cycles	Accuracy	Precision	Recall	F-score
1	94.16%	93.55%	93.90%	93.73%
2	96.27%	95.87%	95.69%	95.78%
3	96.27%	95.87%	95.69%	95.78%
4	96.27%	95.87%	95.69%	95.78%
5	96.32%	95.93%	95.76%	95.85%
6	96.32%	95.93%	95.76%	95.85%
7	96.32%	95.93%	95.76%	95.85%

Table 6.4 String grouping performance for multiple cycles of representative trajectories.

Number of cycles	Accuracy	Precision	Recall	F-score
1	50.54%	75.77%	52.37%	61.93%
2	95.63%	95.50%	95.60%	95.55%
3	97.11%	96.96%	96.95%	96.96%
4	97.11%	96.96%	96.95%	96.96%
5	97.11%	96.96%	96.95%	96.96%

The grouping evaluates similarities between frequent trajectories and representative trajectories. The frequent trajectories may include more than one cycle of a movement, and hence, could be longer than the representative trajectories in Table 6.1. Evaluating grouping performance with multiple cycles allow to identify the number of cycles included in frequent trajectories, as well as an optimum numbers of representative trajectory cycles for grouping.

The vector grouping performs equally well with one or multiple cycles of representative trajectories. This is expected due to the similarity measure based on the cosine similarity, which evaluates length normalized vectors.

The string grouping uses longest common subsequence as a similarity measure and is dependent on the number of elements in each string, especially in situations where the elements are repeated. The results in Table 6.4 show a substantial increase in accuracy from one to two cycles. This indicates that a large number of frequent trajectories in the data set involve two cycles of the movement. The accuracy stabilizes at three cycles, indicating that the frequent trajectories in the data set has a maximum of three cycles.

The number of cycles in the frequent trajectories of a new data set cannot be predicted. Therefore, a conclusion on an optimum number of cycles for grouping can only be made for this data set. However, the computational cost of using a large number of cycles is minimal while the performance remains stable. A large number of cycles, say five or more can be recommended.

6.4.4 Per-group assignment using optimum parameters

The performance of the per-group assignment to groups T1 to T10 and undefined were examined at the optimum number of cycles for representative trajectories.

- **Vector grouping** has an accuracy of above 90%, with T9 the lowest at 90.04%. The other performance measures for the grouping varies substantially between groups, with groups T1 to T4 having high recall (100%), and groups T5 to T8 having high precision (above 96%). The performance is the lowest for the undefined group where the precision, recall, and F-score are 33.55%, 42.62%, and 37.55% respectively (Table 6.5).

- **Multiset grouping** has an accuracy of above 98.5% for groups T1 to T10 with the undefined group having a lower accuracy at 97.5%. The other performance measures for the per group assignment to groups T1 to T10 are also high with the lowest precision (94.65%) for group T6 and the lowest recall (93.38%) and F-score (95.92%) for group T10. The performance is again the lowest for the undefined

group where the precision, recall, and F-score are 79.83%, 77.87%, and 78.84% respectively (Table 6.6).

- **String grouping** has an accuracy of above 98.9% for groups T1 to T10, with the exception being the undefined group at 98.28%. The other performance measures for the per group assignment to groups T1 to T10 are also high, with the lowest precision (94.65%) for group T6, and the lowest recall (93.38%) and F-score (94.95%) for group T10. The performance remains the lowest for the undefined group where the precision, recall, and F-score are 82.22%, 90.98%, and 86.38% respectively (Table 6.7).

Table 6.5 Per-group assignment of vector grouping with 1 cycle of the representative trajectories.

Tactical movement group	Accuracy	Precision	Recall	F-score
T1	97.69%	80.08%	100.00%	88.94%
T2	98.68%	87.20%	100.00%	93.16%
T3	96.76%	76.09%	100.00%	86.42%
T4	98.23%	72.09%	100.00%	83.78%
T5	94.55%	96.77%	45.45%	61.86%
T6	92.59%	98.59%	48.44%	64.97%
T7	95.09%	100.00%	42.86%	60.00%
T8	93.82%	100.00%	36.68%	53.68%
T9	90.04%	53.37%	86.84%	66.11%
T10	92.54%	49.82%	91.39%	64.49%
Undefined	91.51%	33.55%	42.62%	37.55%

Table 6.6 Per-group assignment of multiset grouping with 5 cycles of the representative trajectories.

Tactical movement group	Accuracy	Precision	Recall	F-score
T1	99.80%	97.93%	100.00%	98.95%
T2	99.80%	97.87%	100.00%	98.92%
T3	99.51%	95.87%	99.52%	97.66%
T4	99.85%	96.88%	100.00%	98.41%
T5	99.26%	95.07%	97.47%	96.26%
T6	98.92%	94.65%	97.92%	96.26%
T7	99.61%	100.00%	95.43%	97.66%
T8	99.66%	98.98%	97.49%	98.23%
T9	99.31%	99.54%	94.30%	96.85%
T10	99.41%	98.60%	93.38%	95.92%
Undefined	97.50%	79.83%	77.87%	78.84%

Table 6.7 Per-group assignment of string grouping with 3 cycles of the representative trajectories.

Tactical movement group	Accuracy	Precision	Recall	F-score
T1	100.00%	100.00%	100.00%	100.00%
T2	100.00%	100.00%	100.00%	100.00%
T3	99.95%	100.00%	99.52%	99.76%
T4	100.00%	100.00%	100.00%	100.00%
T5	99.26%	95.07%	97.47%	96.26%
T6	98.92%	94.65%	97.92%	96.26%
T7	99.61%	100.00%	95.43%	97.66%
T8	99.66%	98.98%	97.49%	98.23%
T9	99.26%	99.08%	94.30%	96.63%
T10	99.26%	96.58%	93.38%	94.95%
Undefined	98.28%	82.22%	90.98%	86.38%

Similar to the classification experiments in Chapter 5, the lowest performances were observed with the undefined group. This is expected as frequent trajectories in this group did not show underlying tactical similarities, and instead, were trajectories that did not belong to any other group.

Groups T1 to T4 all indicated high recall values (100% in most cases). This implies that most, if not all, inputs belonging to these groups were identified correctly (no false

negatives) indicating that the frequent trajectories belonging to these four groups were well defined. These four groups are movements to corners of the court, and it is likely that domain expert classification annotated repeated movements to each corner exclusively. Such a clear definition would allow a high recall value. This definition is exemplified further in the 100% precision value for these groups in string grouping.

6.4.5 Implications in automated tactical analysis

The results in Chapter 5 identified classification as a potential method for analyzing badminton tactical indicators. The purpose of developing this grouping approach was to eliminate the reliance on training data encountered with classification.

6.4.5.1 Comparison of classification and grouping approaches

The performance of vector classification and string grouping performed the best in the two respective methods (Figure 6.4). McNemar test [207, 208] was performed in order to check the statistical differences between these two approaches. The result revealed no statistical significant difference (P-value = 0.198) between the two. This implies that the best grouping performance is comparable to the best classification performance and that string grouping can be used instead of vector classification. Additionally, using the grouping approach for tactical indicator analysis eliminates the overfitting issues discussed in Chapter 5.

Figure 6.4 Performances of the classification and grouping experiments.

6.4.5.2 Eliminating the need for training data

The results above confirm the ability of string grouping to perform at a comparable level to vector classification, and hence, replace classification in the tactical indicator analysis step of automated badminton tactical analysis.

There is a clear difference between the underlying principles of classification and grouping using representative trajectories. Classification uses training data and is highly dependent on the availability and quality of this training data. In contrast, the grouping approach eliminates the requirement for training data, and instead requires the definition of a representative trajectory for each group, which can be easily and efficiently defined. Therefore, the grouping approach offers an advantage in terms of efficient adaptability.

6.5 Summary

This chapter builds on the work reported in Chapter 5 where a classification approach was proposed to analyze frequent trajectories of badminton players. The goal was to enhance the classification approach in order to eliminate the reliance on training data.

A grouping approach was proposed to assign badminton frequent trajectories to tactical movement groups based on their similarity with representative trajectories. The ten tactical movement groups defined for classification were maintained, and ten representative trajectories were defined to represent each of these groups. The frequent trajectory representations used for classification (strings, multisets, vectors) were also maintained. Three similarity measures (equations 6.6, 6.12, and 6.19) based on the characteristics of the representative trajectories were defined for grouping.

Three experiments were conducted to evaluate grouping with each representation, where results of automated grouping were compared against manual classification by a domain expert. String grouping achieved the best results, at 97.11% accuracy, 96.96% precision, 96.95% recall, and 96.96% F-score. Using a large number of cycles for representative trajectories is the safer option to use in grouping badminton frequent trajectories.

String grouping had a comparable performance to vector classification, and hence, can replace classification in the tactical indicator analysis step of automated tactical analysis. Using the grouping approach also negates the possible overfitting issue of vector classification. Therefore, using the grouping approach for tactical indicators analysis, instead of classification eliminates the reliance on training data and allows for efficient adaptability.

CHAPTER 7

Tactical data visualization: Player tactical profile generation

Efficient comprehension of information is dependent on an individual's familiarity with the manner in which it is presented [74]. This is because, when information is provided in a form that is familiar, it allows comprehension without the requirement for further questioning or clarification. Hence, information should be presented to a decision maker in a manner that is familiar to him/her [75]. This is the same in tactical analysis, where tactical information must be visualized in a manner that allows efficient comprehension by coaches and athletes.

In the previous two chapters, several approaches were proposed for analyzing badminton tactical indicators. The resulting information requires being visualized in a manner that allows efficient comprehension by domain experts. With this in mind, this chapter attempts to tackle the 5th research question presented in Section 1.4.

- Can the underlying tactics and strategies be visualized in a manner that allows efficient comprehension?

7.1 Introduction

Humans make decisions based on available data, both of past events (prior knowledge) as wells as sensory data of the present situation. The human ability to deduce optimal solutions, based on sensory information, is reliant upon the availability of prior knowledge [54, 58, 59]. This is because, the comparison of new sensory data against prior knowledge provides a basis for accurate anticipation, formulation of strategies and decision making. This is fundamental to tactical analysis, where athletes and coaches may modify tactical decisions, by comparing tactical data from previous matches against observations of the current match.

However, in order to compare tactical information, domain experts must first comprehend tactical data of previous matches. Studies have shown that human comprehension is dependent on the manner in which information is presented [74]. If information is presented in a manner that is familiar, then it can be understood without the need for further clarification. Hence, the tactical data must be presented to domain experts in a manner that allows efficient comprehension as well as comparison.

An evaluation of tactical indicator processing and visualization in Section 2.2.3.2, did not identify any studies documenting the advantages or disadvantages of visualization methods. In fact, not many studies focused on the presentation format of tactical data. Instead, the results of tactical analysis had often been presented as numerical tables, or standard line, bar, and scatter plots. While this format of presentation is adequate, it cannot be considered efficient. This is especially true in the time constrained environment of badminton, where a domain expert may only have seconds to glance at the tactical information.

A study on tennis, where tactical indicators were presented as numerical tables also used a radar plot to visualize the same data [97]. The percentages of tactical indicators were represented on a radar plot, allowing multiple overlays and quick comparisons between data sets. Additionally, different features of a single data set could be easily compared at a glance. Another study on tennis [76] used the field of play to visualize spatio-temporal

information. This form of visualization allows efficient comprehension by a domain expert, as they are familiar with player movements on the field of play.

This chapter aims to visualize the grouped tactical indicators, in order to allow efficient comprehension as well as inter and intra match comparisons by a domain expert. A combination of using a radar plot and the field of play is proposed for this task with modifications based on the badminton tactical analysis domain.

7.2 Overview of work

Figure 7.1 illustrates the flow of work documented in this chapter.

Figure 7.1 Overall flow of work documented in Chapter 7.

The classified frequent trajectories were visualized in order to understand their underlying tactical implications. Different visualization methods are discussed and improvements proposed for efficient examination and comprehension. In Section 7.3.1, traditional methods of tactical data visualization are discussed. Section 7.3.2 proposes the use of normalized radar plots for visualization. Section 7.3.3 proposes subgroups for the tactical movement groups and normalization of data with respect to these subgroups, in order to enhance the visualization. Finally, Section 7.4 discusses two case studies, where classified frequent trajectories from multiple badminton matches are visualized and examined for their underlying tactical implications.

7.3 Visualization of grouped tactical indicators

Badminton is a reactive sport. A badminton player moves to a location on his/her side of the court, and hits the shuttlecock to a region on the opponents' side of the court. The opponent reacts to this shot by moving to intercept the shuttlecock. Hence, a players' movements on court are dictated by the opponent.

The frequent trajectories (tactical indicators) represent frequently repeated movements by a badminton player on the tactical cellular space of a badminton court. However, the reactive nature of badminton implies that these movements were caused by the opponent. Hence, the frequent trajectories and the visualization of grouped frequent trajectories of a player reflects the tactics used by his/her opponent.

In this section, the visualization of frequent trajectories are examined and tactics discussed. The goal is to identify a visualization method that allows a domain expert to examine and comprehend the underlying tactical implications efficiently. Section 7.3.1 starts with the traditional approaches identified in Section 2.2.3.2. Improvements are suggested in sections 7.3.2 and 7.3.3 to allow efficient examination and comprehension.

7.3.1 Traditional data presentation

First, the example of frequent trajectory visualization in Section 5.4.5.2 is revisited. 307 frequent trajectories were classified to ten tactical movement groups (T1 to T10) and as undefined. The results of this classification are in Table 7.1.

Presentation of results in tabular form provides the most accurate information allowing examination in detail. However, this method does not allow efficient identification of tactical preferences. In Table 7.1, the preference in using tactics T3 and T4 is clear while none of the other tactical patterns can be examined or compared at a glance. Tactics T3 and T4 can only be identified because of their high frequency.

Table 7.1 Classified frequent trajectories.

Tactical movement group	Number of classified frequent trajectories	Percentage
T1	31	10.10%
T2	22	7.17%
T3	73	23.78%
T4	65	21.17%
T5	11	3.58%
T6	17	5.54%
T7	16	5.21%
T8	13	4.23%
T9	29	9.45%
T10	25	8.14%
Undefined	5	1.63%
Total	**307**	**100.00%**

Next, the classification results were visualized as a bar graph and compared with respect to tactical movement groups (Figure 7.2). This visualization allows comparison of intra match tactics in order to identify tactical preferences.

In a visual examination of the bar graph in Figure 7.2 (a), tactics T3 and T4 are prominent. Additionally, tactics T1, T2, T9 and T10 have been used more often than tactics T5 to T8.

The tactical movement groups represented on the badminton court (Figure 7.2 (b)) allows to understand tactical implications. Tactics T1, T3, and T9 (which move the player to cells 1, 3 and on the diagonal between cells 1 and 3), have been used more often that their opposites, T2, T4 and T10 (which moves the player to cells 2, 4 and on the diagonal between cells 2 and 4).

Figure 7.2 Visualization of classified frequent trajectories in Figure 5.4. (a) Classified frequent trajectories in graphical form. (b) Tactical movement groups from Figure 5.2.

However, further inclusion of data from multiple matches would clutter the bar graph, and complicate inspection of both intra and inter match tactics. This is illustrated in Figure 7.3 where frequent trajectories of a player in two separate matches (Table 7.2) have been visualized. The use of tactic T1 in match 1 is prominent. Beyond this, the visualization requires careful examination to identify intra and inter match tactics. The visualization requires improvement, allowing efficient inter match comparisons.

Figure 7.3 Visualization of classified frequent trajectories from multiple matches as a bar graph.

Table 7.2 Classified frequent trajectories of multiple matches.

Tactical movement group	Match 1		Match 2	
	Classified frequent trajectories	Percentage	Classified frequent trajectories	Percentage
T1	63	35.80%	13	8.67%
T2	15	8.52%	25	16.67%
T3	25	14.20%	36	24.00%
T4	18	10.23%	16	10.67%
T5	12	6.82%	7	4.67%
T6	6	3.41%	19	12.67%
T7	8	4.55%	5	3.33%
T8	3	1.70%	9	6.00%
T9	11	6.25%	14	9.33%
T10	10	5.68%	5	3.33%
Undefined	5	2.84%	1	0.67%
Total	**176**		**150**	

7.3.2 Normalized radar plots

A radar plot and plot overlays can be used for efficient visual inspection and comparisons. However, overlays of two data sets with different numbers of data points (classified frequent trajectories) do not allow comparisons. In order to allow overlays and accurate comparisons, the classified frequent trajectories were normalized according to the total number of frequent trajectories (percentage of frequent trajectories) in each group. These normalized values were plotted on a radar plot.

Note: In the discussions in this section, the undefined group has been excluded as it does not serve a purpose in identifying tactics.

First, the normalized values in Table 7.1 were visualized as a radar plot (Figure 7.4). This plot can be examined at a glance to identify the prominence of tactics T3 and T4. Additionally, tactics T1, T3 and T9 having higher frequencies than T2, T4 and T10 is

identifiable. Hence, this form of visualization is similar in efficiency to the bar graph when visualizing data from one match and evaluating intra match tactics.

Figure 7.4 Normalized radar plot. (a) Normalized values of classified frequent trajectories visualized in a radar plot. (b) Tactical movement groups from Figure 5.2.

Next, inter match comparisons were examined. The normalized values in Table 7.2 were visualized on a radar plot in Figure 7.5. The axis values have been eliminated, providing a clear image for visual tactical comparisons. This radar plot can be easily examined to identify the prominent use of tactic T1 in match 1 as opposed to tactics T2 and T3 in match 2. Further examination identifies a higher frequency in using tactics T6 and T9 during match 2.

However, while examining the visualization of tactic T1 to T4 was easy, examination of tactics T5 to T10 was difficult. The radar plot was skewed towards tactics T1 to T4, due to the high number of frequent trajectories classified to these tactical movement groups. This trend of tactics T1 to T4 being used more often was also observed in all previous visualizations as well as the numerical data in Tables 7.1 and 7.2. The visualization requires improvement, allowing efficient examination of all tactics.

Figure 7.5 Visualization of normalized, classified frequent trajectories from multiple matches as a radar plot.

7.3.3 Normalized subgroup radar plot

The tactical movements were separated to three subgroups. Movements to corners (T1 to T4), linear movements along the sides top and bottom (T5 to T8), and diagonal movements (T9 and T10). The frequent trajectories classified to each group were normalized according to the respective subgroup. In order to account for the smaller number of movements in the diagonal subgroup (2), compared to the other two subgroups (4), the normalized value of T9 and T10 were halved. This modification allows better visualizations of frequent trajectories classified to all ten tactical movement groups.

The classified frequent trajectories of a player in two separate matches from Table 7.2 were normalized according to subgroups in Table 7.3. These normalized values were visualized on a radar plot in Figure 7.6.

Table 7.3 Classified frequent trajectories of multiple matches normalized according to subgroups.

Tactical movement group	Subgroup	Match 1		Match 2	
		Classified frequent trajectories	Percentage per subgroup	Classified frequent trajectories	Percentage per subgroup
T1	Corners	63	52.07%	13	14.44%
T2		15	12.40%	25	27.78%
T3		25	20.66%	36	40.00%
T4		18	14.88%	16	17.78%
T5	Linear	12	41.38%	7	17.50%
T6		6	20.69%	19	47.50%
T7		8	27.59%	5	12.50%
T8		3	10.34%	9	22.50%
T9	Diagonal	11	26.19%	14	36.84%
T10		10	23.81%	5	13.16%
Total		**171**		**149**	

Figure 7.6 Visualization of classified frequent trajectories, normalized according to sub groups, from multiple matches.

This visualization allows to quickly identify tactical differences between two matches. In match 1, the corner subgroup tactic T1 was preferred, while in match 2, T2 and T3 were preferred. In the linear subgroup, in match 1, T5 and T7 were preferred, while in match 2, T6 was preferred. The T9 diagonal subgroup tactic was used more than T10 in both

matches, although, the reliance on tactic T9 increased from match 1 to match 2. The radar plot allows efficient examination and comprehension of all tactical movement groups, and hence, can be considered a player tactical profiles.

However, the limitations caused by normalization must be noted. The subgroup normalization adversely affects inter subgroup examination. For example, in Figure 7.6, tactics T1 in match 1 and T6 in match 2 appear to occur at a similar frequency. However, this is not the case, and the frequencies are 63 and 19 respectively. Fortunately, this limitation only applies to inter subgroup examination, and intra subgroup examination is not affected. Being mindful of this fact and refraining from inter subgroup examinations allow this visualization to be used in inter match examinations. If detailed intra subgroup or intra match analysis is required, the normalized radar plot discussed in the previous section can be used.

7.4 Discussion of case studies

This section discusses two case studies of badminton tactical analysis. Multiple badminton matches were analyzed and the resulting classified frequent trajectories visualized as player tactical profiles. As discussed in the previous section, the tactical profiles are radar plots of classified frequent trajectories, normalized according to the subgroups.

7.4.1 Case 1: One player against multiple opponents

Multiple matches of one player were analyzed to evaluate his tactical tendencies against opponents. The tactics were compared with respect to the handedness of the opponents. The player was ranked within the world's top 20 at the time of recording these matches. The results of the frequent trajectory classification is in Table 7.4. The player tactical profile is in Figure 7.7 (a).

Table 7.4 Classified frequent trajectories of a badminton player against multiple opponent, normalized according to subgroups. *Note: TMG is tactical movement groups.*

TMG	Right handed opponents		Left handed opponents	
	Freq traj	% per subgroup	Freq traj	% per subgroup
T1	108	24.27%	37	16.23%
T2	90	20.22%	66	28.95%
T3	135	30.34%	94	41.23%
T4	112	25.17%	31	13.60%
T5	40	28.99%	16	26.67%
T6	36	26.09%	23	38.33%
T7	29	21.01%	10	16.67%
T8	33	23.91%	11	18.33%
T9	69	23.31%	36	32.14%
T10	79	26.69%	20	17.86%
Total	**731**		**344**	

Figure 7.7 Player tactical profile. (a) Radar plot of one players' tactics against multiple opponents. (b) Tactical movement groups from Figure 5.2.

Examination of the tactical profile illustrates the differences in tactics used against right and left handed opponents. Against right handed opponents, all tactics are used in a uniform manner. However, against left handed opponents, tactics T2, T3, T6 and T9 were prominent. These tactics move left handed opponents to the top right (cell 2), back right (cell 3), on the right side (cell 2 to 3) and along the diagonal (cell 1 to 3). The movements

in using these tactics are illustrated in Figure 7.8, and show a clear preference to keep left handed opponents on the right side of the court.

Another feature of this tactical profile is the relative reluctance in using tactics T4, T5, T8 and T10 against left handers. All of these tactics involve the back left (cell 4). T5 had been used somewhat, while there is a clear reluctance to use the other three. This shows a reluctance in sending left handed opponents to cell 4 when other options are available.

With this knowledge, a left handed opponent of this player could be advised to anticipate movements on the right side of the court. This would allow the opponent to focus on the right side as well as shift his neutral stance to facilitate quicker reactions to move right. Additionally, the opponent could pay less attention in preparing to move to cell 4. This would allow him to focus on the other regions of the court, once again gaining an advantage in reaction time.

Figure 7.8 Preferred tactics against left handed opponents.

7.4.2 Case 2: Two players against each other

Two matches between the same two players played within a few days of each other were analyzed. The goal was to evaluate the strategic changes made by the two players from one match to the next. Both players were ranked within the world's top 50 at the time of

recording the matches. The results of the frequent trajectory classification is in Table 7.5. The player tactical profile is in Figure 7.9 (a).

Table 7.5 Classified frequent trajectories of two players against each other in two separate matches, normalized according to subgroups. *Note: TMG is tactical movement groups.*

TMG	Player 1				Player 2			
	Match 1		Match 2		Match 1		Match 2	
	Freq traj	% per subgroup	Freq traj	% per subgroup	Freq traj	% per subgroup	Freq traj	% per subgroup
T1	11	10.19%	20	24.10%	63	52.07%	13	14.44%
T2	9	8.33%	13	15.66%	15	12.40%	25	27.78%
T3	49	45.37%	24	28.92%	25	20.66%	36	40.00%
T4	39	36.11%	26	31.33%	18	14.88%	16	17.78%
T5	6	23.08%	5	16.13%	12	41.38%	7	17.50%
T6	7	26.92%	10	32.26%	6	20.69%	19	47.50%
T7	6	23.08%	10	32.26%	8	27.59%	5	12.50%
T8	7	26.92%	6	19.35%	3	10.34%	9	22.50%
T9	11	25.00%	18	28.13%	11	26.19%	14	36.84%
T10	11	25.00%	14	21.88%	10	23.81%	5	13.16%
Total	**156**		**146**		**171**		**149**	

An examination of overall strategies of both players in matches 1 and 2 show that the strategy of player 1 remained relatively stable and consistent while the strategy of player 2 drastically changed from match 1 to match 2. Player 1 defeated player 2 in both occasions. It stands to reason that having lost the first match, player 2 decided to use a drastically different strategy in match 2. However, player 1 did not drastically change his successful strategy from match 1 to match 2, and instead, made minor modifications based on his performance in the first match.

The biggest change made by player 1 from match 1 to 2 was the reduction in using tactic T3 and increasing the use of tactic T1. This change makes player 2 move more often to cell 1 (front of the court) instead of cell 3 (back of the court).

Player 2 made drastic changes from match 1 to 2. In match 1, tactics T1, T5 and T7 were used prominently, where player 1 was moved to the front left, along left and front of the court (Figure 7.10 (a)). In match 2, tactics T3, T6 and T9 were used prominently,

moving player 1 to the back right, along the right, and along the diagonal from back right to front left(Figure 7.10 (b)).

This information allows understanding the overall strategies used by each player, and the changes they have made from match to match. Additionally, the knowledge of individual tactics used during each match would allow efficient anticipation, as well as advantages in reaction times, similar to those discussed previously in case 1.

Figure 7.9 Player tactical profiles. (a) Radar plots of two players against each other in two separate matches. (b) Tactical movement groups from Figure 5.2.

Figure 7.10 Preferred tactics of player 2. (a) Match 1. (b) Match 2.

7.5 Summary

This chapter focused on the output from work reported in previous chapters. The previous chapters proposed a method for gathering and analyzing badminton tactical information. This chapter discussed the visualization of analyzed tactical data. Several visualization methods were discussed to identify a method for efficient comparison and comprehension.

First, the traditional approaches of tabulated numerical data and bar graphs for data visualization were discussed. This approach did not allow efficient comparison of tactical information.

Next, the classified frequent trajectories were normalized according to tactical movement groups and visualized on a radar plot. This allowed efficient detailed intra match tactical comparisons. However, inter match tactical comparisons with plot overlays were difficult. This was because badminton players used tactics T1 to T4 more often than the other tactics. This resulted in a skewed radar plot where differences in tactics T5 to T10 between overlays were difficult to examine.

Finally, three subgroups (corners, linear and diagonal) for the tactical movements were proposed. The classified frequent trajectories were normalized according to the subgroups,

and visualized on a radar plot. This approach allowed efficient examination of inter match tactics on plot overlays.

The radar plots can be used as player tactical profiles for efficient visual examination and comparisons of tactical information. The tactical preferences and strategies of a badminton player can be identified from the radar plots and understood by domain experts. The tactical movement groups represented on badminton courts can enhance comprehension of underlying tactical implications. This was exemplified in the discussion of case studies, where tactically useful information were identified from the tactical profiles.

CHAPTER 8

Conclusion

8.1 Looking back

Rising popularity and funding for sports have increased the demands on coaches and athletes to maintain a high level of performance. The coaching structure has expanded to cater to this demand with the inclusion of scientists and systematic approaches for performance evaluation and maintenance. Technologist have also joined the ranks of this community by developing tools to assist the tasks performed by scientist.

Sports scientists evaluate four main types of performance; physiological, psychological, technical and tactical. The first three types of performances are evaluated following a match and feedback provided to athletes and coaches. On the other hand, tactical analysis can be performed during the game itself and feedback provided during the game, resulting in a more immediate impact.

Sports tactical analysis is a sub category of sports performance analysis, and published work on performance analysis were comprehensively reviewed in Chapter 2. Performance analysis is the evaluation of athletic performance during a game used as a tool for evidence based decision making. It is based on the fundamentals developed in notational analysis,

where performance indicators are manually annotated and analyzed by domain experts. Tactical analysts gather what are called tactical indicators in order to analyze tactical performance.

Tactical indicators vary depending on the sport. However, they can all be divided into three groups of latent information, position, action and time. In manual notational analysis, the tactical indicators are annotated by human agents. In contrast, automated methods gather latent information, from which tactical indicators are extracted. These tactical indicators are then analyzed in order to understand the underlying tactical implications and strategies. Finally, the analyzed tactical information is presented to a coach, allowing tactical decision making.

The work documented in this thesis sought to develop a comprehensive automated approach for tactical analysis in badminton. The following research questions were identified (Section 1.4) and addressed.

1. How can tactical information of badminton players be automatically gathered at international tournament environments?

2. How can tactical indicators be extracted from the automatically gathered tactical information?

3. Can the tactical indicators be analyzed in order to easily comprehend their underlying tactics?

4. Can the analysis method easily be adapted to domain requirements in badminton tactical analysis?

5. Can the underlying tactics and strategies be visualized in a manner that allows efficient comprehension?

8.2 Addressing research questions

This section summarizes how the work presented in this thesis addressed above mentioned research questions.

1. How can tactical information of badminton players be automatically gathered at international tournament environments?

It was identified according to literature (Section 2.4.1) that automated data gathering in international sports have used computer vision and image processing approaches. This was because competing teams would not allow opposing teams to place sensors on the bodies of athletes. A review of computer vision based approaches used for automated data gathering in badminton (Section 2.4.1.2) found that detecting actions or inferring actions through tracking the shuttlecock was unreliable. This was due to the angle of video capture possible at international tournament environments. The player positions were identified as the most suitable latent tactical information to be gathered. Image subtraction was identified to be the most suitable method for identifying player positions.

In Chapter 3, an image processing algorithm was proposed for player position detection on badminton video footage captured at international tournaments by a competing team. The court region was extracted through manually annotating the court corners on the first frame of the video. The image processing steps segmented the two players on a binary image. The pixel coordinates of the players were calculated, and calibrated to real-world coordinates using the manually annotated information from the first frame of the video.

The occurrence of occlusion in badminton was examined, where a combined segment was identified instead of two separate segments representing each player. It was identified that occlusion only took place at the front of the court (near the net) and that players do not move latterly together after occlusion. An occlusion handling approach was proposed based on these findings. The bounding boxes of the frame preceding occlusion was used to

separate the combined segment. These separated segments were used to identify separate player positions.

The proposed image processing algorithm and the occlusion handling method can be used to automatically gather latent player positions (x and y coordinates) from badminton video footage captured at international tournaments.

2. How can tactical indicators be extracted from the automatically gathered tactical information?

The automatically gathered latent tactical information were the x and y coordinates of player positions. Tactical indicators were to be extracted from this data. A review of tactical indicators used for notational analysis (Section 2.3) identified that in tactical analysis, latent position information is represented with respect to tactically important cells on a playing field. A review of tactical indicators used in badminton notational analysis (Section 2.3.2.3) identified that the tactical cellular space used in badminton varied from study to study. Furthermore, the tactical cellular space had not been quantified and no reasons were provided as to the number of tactical cells used.

Chapter 4 defined the optimum tactical cellular space for badminton through domain expert feedback as well as reasoning based on the game of badminton. A nine cell arrangement was proposed and experiments were conducted to identify the borders of this cellular space. It was found that x and y coordinates of player positions had marginal fluctuations causing inconsistent annotations on the tactical cells. An annotation method called the dynamic window was proposed to negate these fluctuations. This approach allowed the automated annotation to replicate the intuitive manual annotation of a badminton tactical analyst.

The x and y coordinates were annotated on this tactical cellular space. The player trajectories as they transition on this cellular space were extracted. These trajectories were represented as numerical strings where the characters of the string represented cell labels and the sequence represented transition order. From these numerical strings, frequently

repeated trajectories were extracted by identifying common substrings. An examination of these frequent trajectories showed that each of them described tactical features while a large collection had the potential to describe underlying strategies of a game.

The defined tactical cellular space, identified court cell borders and the dynamic window annotation method can be used to provide a tactical structure to the latent position data. Player trajectories on this tactical structure can be extracted from which frequent trajectories can be identified. These frequent trajectories describe tactical features of badminton and can be considered tactical indicators.

3. Can the tactical indicators be analyzed in order to easily comprehend their underlying tactics?

The tactical indicators in this study were the frequent trajectories of badminton players. These trajectories were to be analyzed in order to understand their underlying tactics. A review of approaches used for automated tactical information processing (Section 2.4.2) found no prior studies on the sport of badminton. Based on studies conducted for other sports, machine learning was identified as a potential avenue for exploration in badminton. Unsupervised machine learning had the advantage of detecting hidden tactical features, although, this was redundant when the tactical features could be defined. Unsupervised learning also did not allow inter match analysis. Supervised machine learning was identified as the best approach, given its ability for inter match comparisons with defined tactical features.

Chapter 5, examined the underlying principles of supervised classification algorithms in order to identify the best suited algorithm for badminton tactical analysis. The k nearest neighbor (kNN) algorithm was identified as the best due to it being a lazy learner where no training time is needed. This algorithm had the added benefit of being less complex when explaining to a badminton domain expert without technical background in technology. Ten tactical movement groups (classes) were defined for classification based on domain expert feedback. Each movement group represented a distinct movement in badminton,

with tactical implications familiar to domain experts. Three representations were proposed for frequent trajectories (strings, multisets and vectors), and similarity measures were identified for classification. The vector representation, using cosine similarity as the similarity measure produced the best classification results among the three representations.

Frequent trajectories of one badminton match were classified to ten tactical movement groups and the results were visualized as a bar graph. This visualization allowed intra match tactical comparisons, as well as efficient understanding of tactical preferences of an individual badminton player during the match.

The kNN algorithm and cosine similarity can be used to classify frequent trajectories (tactical indicators) to ten tactical movement groups. The classified information can be used to easily comprehend underlying tactics and strategies of badminton.

4. Can the analysis method easily be adapted to domain requirements in badminton tactical analysis?

In Chapter 5, the kNN classification algorithm was identified as the best choice for badminton tactical analysis after examining its underlying principles. The lazy learner algorithm that required no training time was identified as an advantage in badminton tournament environments. The tactical movement groups were defined through domain expert feedback, in order to ensure their underlying tactical implications were familiar to these domain experts. However, the classifiers reliance on training data was identified as a hindrance in badminton tactical analysis.

Chapter 6 proposed an enhanced grouping methodology to eliminate the reliance on training data. Frequent trajectories were to be assigned to the same ten tactical movement groups without training a classifier. Ten representative trajectories, each representing a tactical movement group was defined. This definition was efficient and could be repeated if classes were to be modified. The representations used for frequent trajectories in Chapter 5 were maintained, while the similarity measures were modified based on characteristics of representative trajectories.

The string representation, using a similarity measure based on the longest common subsequence showed the best performance. While this performance was marginally below the vector classification, there was no significant difference between the two. Therefore, this enhanced grouping method, which successfully eliminated the reliance on training data, could be used instead of the classification method.

5. Can the underlying tactics and strategies be visualized in a manner that allows efficient comprehension?

The classified frequent trajectories represent the underlying tactics of badminton. This underlying tactical information must be visually represented, in order to allow efficient comparisons and comprehension by domain experts. A review of fundamentals in tactical data processing in Section 2.2.3.2 identified no specific visualization methods that could be considered optimal. Tactical analysis results were traditionally visualized as numerical tables and bar graphs.

Chapter 7 examined several approaches for classified frequent trajectory visualization. Numerical tables, bar graphs and normalized radar plots all had various deficiencies in either intra match or inter match data comparison. Examination of normalized radar plots identified that the classified data was skewed due to badminton players using tactical movements T1 to T4 more frequently than the others. This hindered the inter match comparison of classified frequent trajectories on normalized radar plots.

The tactical movement groups were divided into three subgroups and the classified results normalized with respect to these groups. This normalization amplified the data classified to lesser used tactical movement groups. This data was then visualized on a radar plot allowing efficient comparisons of intra and inter match tactics and strategies. Discussion of two case studies exemplified this ability. Furthermore, comprehension of tactics was enhanced with tactical movement groups represented on a badminton court.

The underlying tactical information (classified frequent trajectories) can be normalized according to tactical movement subgroups and visualized on a radar plot. This allows

efficient visual comparison of the tactical information. The use of tactical movement groups represented on a badminton court can enhance comprehension of tactical information.

8.3 Summary of contributions

The work documented in this thesis aimed to develop a comprehensive approach for automated tactical analysis in badminton. The above mentioned research questions were addressed to achieve this goal. This section summarizes the key contributions arising from addressing each research question.

8.3.1 Automation of tactical analysis

In order to automate badminton tactical analysis, the domain of performance analysis was extensively examined in the literature review in Chapter 2. This chapter provided insights on the fundamentals of performance analysis and how these fundamentals have been adapted for use with technology in automating tactical analysis. This survey identified automated latent tactical information gathering, extraction of tactical indicators, subsequent analysis and presentation as the steps required in an automated system. Manual tactical analysis of various sports was evaluated to identify the types of tactical indicators used. Automated approaches used for tactical data gathering and analysis were evaluated to identify suitable approaches for the problem at hand.

8.3.2 Automated player position detection in badminton

Section 2.4.1.2 identified the appropriateness of using an image processing algorithm based on image subtraction for automated data gathering in badminton. An image processing algorithm was proposed for badminton player position detection in Chapter 3. The requirements and constraints present at international badminton tournaments were taken into consideration and the steps involved in the proposed algorithm were kept to a minimum. The occurrence of badminton player occlusion was examined to identify

combined trajectory features in player movement. An approach to handle occlusion was proposed based on these findings.

8.3.3 Badminton tactical indicator extraction

Section 2.3 identified that in tactical analysis, latent position information is represented on a tactical cellular space. Section 2.3.2.3 identified that this cellular space in badminton had not been quantified and no reasons were provided as to the number of tactical cells.

In Chapter 4, domain expert feedback and reasoning based on the reach of a badminton player was used to propose a nine cell arrangement as the optimal tactical cellular space for badminton. The borders of this cellular space were experimentally identified. The annotation of latent position information on this cellular space was examined and an automated method (dynamic window annotation) was developed to negate errors caused by small fluctuations in automated player position detection.

The latent position information was annotated on the tactical cellular space and frequently repeated trajectories extracted. Examination of these frequent trajectories identified them as tactical indicators in badminton.

8.3.4 Badminton tactical indicator analysis

Section 2.4.2 identified that no previous studies were conducted to automatically analyze badminton tactical indicators. Based on automated analysis in other sports, supervised machine learning was identified as the most appropriate approach to be used.

Chapter 5 examined the characteristics of classification algorithms and identified kNN, being a lazy learner, as the best suited algorithm for use at international badminton tournaments. Three factors that can be considered as deficiencies in kNN were identified. Of these factors, the reliance on a similarity measure and the need for an optimum value of k were identified as factors that influence the problem at hand. Experiments were conducted to identify a similarity measure and the optimal value of k for that similarity measure.

Domain expert feedback was used to define ten classes (tactical movement groups T1 to T10) to which badminton tactical indicators (frequent trajectories) could be classified. Three representation (strings, multisets and vectors) for the frequent trajectories were proposed and an appropriate similarity measure was identified for each. Vector representation and the use of cosine similarity as the similarity measure was identified to be the best approach. The optimum value of k for this approach was determined to be 1.

Evaluation of the classified data illustrated its ability to describe underlying tactics and strategies in badminton.

8.3.5 Enhancement of analysis method

Chapter 6 proposed an enhancement for the classification in order to eliminate the reliance on training data. The frequent trajectories was proposed to be assigned to the ten tactical movement groups based on their similarity to a representative trajectory for each group.

Representative trajectories were defined for each groups. Similarity measures identified in Chapter 5 were modified based on the characteristics of the representative trajectories. With this enhancement, the string representation and the use of the respective similarity measure based on the longest common subsequence was identified to be the best approach. While the performance of this approach was marginally below that of the best classification, no statistical significance was found in this difference.

8.3.6 Analyzed data representation

Chapter 7 examined methods to visualize the analyzed tactical indicators (classified frequent trajectories). This examination identified that badminton players utilize tactical movements T1 to T4 more often than T5 to T10.

Based on this finding, the tactical movements were sub divided to three groups (corners, linear and diagonal). The classified frequent trajectories were normalized according to these subgroups, allowing those classified to groups T5 to T10 to be magnified. This information was then visualized on a radar plot and compared against tactical movement

groups represented on a badminton court. The ability of this visualization for badminton tactical analysis was illustrated using two case studies.

8.4 Challenges

Lack of domain experts

The evaluation of results in this thesis were performed against the manual annotation of a single domain expert. This was due to the lack of badminton tactical analysts. Badminton teams are small in number and typically employ a single tactical analysts, which is the case with the Malaysian National Badminton team. Additionally, the domestic team competition structure in Malaysia has not developed to a point where teams employ a tactical analyst. This was also confirmed (by the Malaysian tactical analyst) to be the case with domestic structures of other nations.

Provided we accept the domain expertise of the Malaysian National Badminton Team's tactical analyst, the results discussed in this thesis can be considered accurate. However, evaluation against multiple data sets curated by independent experts would be ideal.

Lack of data sets

The manually annotated data used in this thesis was created by a domain expert. This Malaysian tactical analyst, with a full time job and frequent travels to international badminton tournaments, found it difficult to make time to curate data. This is especially evident in the small set of manually annotated data used to evaluate results in Chapter 4.

No external data sets were available for automated badminton tactical analysis, and due to the lack of studies in automated badminton tactical analysis, this was expected. However, the availability of such external data for experimentation would have been ideal.

8.5 Future work

8.5.1 Player position detection and inference of action indicators

The documented work on this thesis is based on latent position information and related tactical indicators. Chapter 3 documents the development of an image processing algorithm for badminton player position detection. This information was annotated on tactical cells of a badminton court and badminton player trajectories extracted (Chapter 4). The accuracy of the proposed image processing method was adequate for the task of extracting trajectories on the tactical cellular space.

If the accuracy of player position detection was improved, and player trajectories were extracted in two-dimensional space, action indicator extraction could be possible. This was the philosophy behind studies on shuttlecock tracking discussed in Section 2.4.1.2. The goal was to analyze the paths of the shuttlecock, identify locations at which the path ends (badminton players hitting the shuttlecock), and infer the types of shots being played. A similar approach could be used with accurate player trajectories being analyzed instead of the shuttlecock trajectories. The shuttlecock tracking studies were hampered by the difficulty of detecting fast moving shuttlecocks. Using player trajectories instead of the shuttlecock would also nullify this problem.

As a potential method, long range depth sensors could be used instead of standard RGB cameras. They could be fixed at the same location as standard cameras. A competing team would be able to acquire these images and could perhaps improve the accuracy of player position detection.

8.5.2 Tactical indicator extraction

Tactical indicators used in this study were frequently repeated badminton player trajectories as they transition on tactical cells. These trajectories were classified according to their tactical implication and analyzed independent of their opponent.

An interesting improvement would be the analysis of combined player trajectories as they move on this cellular space. The symbolic representation for the trajectories could be modified to include opponent position. The extraction of tactical indicators and subsequent analysis would provide insight into tactical patterns of player pairs. This approach would also be complimentary to the inference of action indicators mentioned above.

8.5.3 Tactical indicator classification

Tactical indicator classification in Chapter 5 was conducted with a data set curated by domain experts. The frequent trajectories were represented as strings, multisets and vectors, and classified using the longest common subsequence, Jaccard index and cosine similarity respectively.

The results of the best classification approach (vector classification) suggested a possible overfit, a lack of independence in the manually classified data, or a clear separation of classes. The lack of independence is possible considering the data was curated by a single tactical analysts. These issues could be further examined, leading to possible improvements of the classification approach.

8.5.4 Tactical indicator grouping

The grouping approach proposed in Chapter 6 is expected to adapt efficiently when tactical movement groups require modification. However, the performance of this approach was only evaluated against the same tactical movement groups. Testing on such modified tactical movement groups require the creation of another data set, and was not possible with the availability of the domain expert. Creation of such a data set and evaluation would further validate this approach and its adaptability.

8.5.5 Automated tactical analysis of badminton

The approach used in this study followed the adaptation of fundamentals used in manual tactical analysis. This approach required gathering latent information, extraction of tactical indicators, as well as analysis and subsequent presentation of results to domain experts.

First, it stands to reason that the second step of tactical indicator extraction could be eliminated. Tactical indicators were gathered in manual annotation, because it was impractical to annotate large quantity of latent information. However, with technological tools, acquiring large quantities of latent information is possible. Approaches for analyzing such large datasets have been tackled in the domain of big data and data mining. Perhaps the application of these approaches could result in discovery of badminton strategies that enhance our understanding of the sport of badminton.

Second, unknown or unexpected tactics could potentially be identified through unsupervised machine leaning. The tactics and strategies resulting from tactical analysis were required to be understood by the domain experts. This was the reason for using supervised learning for tactical indicator analysis, where the classes were pre-defined and easily understood by domain experts. However, unsupervised learning could be used to identify unknown or unexpected features in tactical indicator data sets. If a compelling argument could be made for the benefits of such discoveries, it would result in domain expert acceptance of such methods. These unsupervised approaches could also be complimentary to the analysis of latent information and elimination of tactical indicator extraction mentioned above.

8.5.6 Adaptation to badminton doubles

The work discussed in this study focused on singles badminton. It stands to reason that the same approach could be successfully implemented for doubles.

The player position detection approach requires enhancement in order to identify four players rather than two. The biggest challenge is expected to be in occlusion handling,

where players on the same half of the badminton court (same team) would occlude each other. The trajectory features during occlusion would not be the same as those encountered in this study, and hence, a new occlusion handling method must be developed. Player identification would also be a challenge when players on the same team occlude each other. The players must be separately identified following occlusion, where in some cases they look identical, even to the naked eye watching on television.

The tactical cellular space would likely require modification according to tactics and movements in doubles badminton. The above mentioned symbolic representation for combined player trajectories would efficiently adapt to this situation, where the two players on each team must be considered a pair rather than individuals.

8.6 Concluding remarks

Despite recent development in technology and its application in the sports domain, automated tactical analysis has been relatively under explored. This is especially true in the sport of badminton, where automated tactical data analysis has not been explored at all.

This thesis develops a comprehensive automated approach for badminton tactical analysis, while focusing on the final application and the adaptation of technology by domain experts. Automated latent data gathering, tactical indicator extraction, tactical indicator analysis, and analyzed data visualization have all been addressed. These approaches could be integrated into one system, allowing its application for badminton tactical analysis. The domain expert's understanding of the approaches used in automation should result in acceptance of the technology by badminton coaches and athletes. Future incremental improvements to individual steps, discussed in the previous section, could be completed and integrated to the already accepted system. The use of such a system could also pave the way for advanced technological approaches that are not easily explained to badminton experts being accepted in the sports domain.

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