Application of computer vision and vector space model for tactical movement classification in badminton

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Abstract

Performance profiling in sports allow evaluating opponents' tactics and the development of counter tactics to gain a competitive advantage. The work presented develops a comprehensive methodology to automate tactical profiling in elite badminton. The proposed approach uses computer vision techniques to automate data gathering from video footage. The image processing algorithm is validated using video footage of the highest level tournaments, including the Olympic Games. The average accuracy of player position detection is 96.03% and 97.09% on the two halves of a badminton court. Next, frequent trajectories of badminton players are extracted and classified according to their tactical relevance. The classification performs at 97.79% accuracy, 97.81% precision, 97.44% recall, and 97.62% F-score. The combination of automated player position detection, frequent trajectory extraction, and the subsequent classification can be used to automatically generate player tactical profiles.

1. Introduction

Active sports require a single athlete or a team of athletes to move on a space referred to as a field or a court. These movements are often quantified and analysed with the intention of improving athletic performance and potentially the outcome of the games. The quantified data regarding this movement is commonly used in the analysis of two separate aspects of sports performance. Technique analysis [9] refers to the analysis of performing an action, or how the action was carried out. On the other hand, tactical analysis [5] attempts to evaluate the action that was performed, or what action was carried out, when and where, for its importance in the situation. In this paper we concentrate on the latter, tactical analysis, in the sport of badminton.

Technological methods such as wearable sensors [23, 24, 20], motion capture [17], and video cameras [11, 3, 10] have enhanced the efficiency of spatio-temporal data gathering. However for tactical analysis at international competitions, the technological methods used for data gathering must be unobtrusive, as opponents would not allow sensors to be placed on them. Several high profiles sports such as soccer [3], basketball [10], tennis [25], and squash [21] have used image processing for automated spatio-temporal data gathering. Similarly, an unobtrusive computer vision based approach, capable of gathering data at international badminton tournaments is required for the application.

Tactical analysts in sport divide the field of play or court into tactically important cells [1, 8]. When trajectories of players are represented as transitions from one cell to another, it allows the use of a similarity measure [6, 15] for comparing these trajectories (transition patterns). When applying such an approach in badminton, a technique capable of comparing different transition pattern lengths is required. This is because badminton consists of playing segments called rallies, which are of different lengths (time and cell transitions) depending on the amount of time the players are able to keep the ball (shuttlecock) in the air. However, as the number of tactically important cells on the playing field is constant, the transition patterns can be represented in vector space [18] and an appropriate similarity measure can be used.

This research aims to propose an approach to automate tactical analysis at the highest level international badminton tournaments. First, an image processing algorithm [22] for automated player position detection in badminton was implemented. The player position data is then represented on tactically important cells on a badminton court and the trajectories of badminton players in the form of transition patterns were extracted. Next, frequently repeated trajectories were identified, represented in vector space, and classified according to their tactical relevance using a similarity measure. The classified data allows the generation of tactical movement profiles and the visualisation of badminton tactics. The image processing algorithm was validated using video footage captured at international badminton tournaments, and the performance of the classification approach was evaluated against a domain expert.

2. Materials and methods

Video footage captured at international badminton tournaments were obtained from the video library of the National Sports Institute of Malaysia. The videos were captured from a camera placed behind the court at an elevated angle from ground level (same view as televised badminton matches) with the playing field in full and unobstructed view.

The image processing algorithm and player trajectory extraction were implemented using National instruments LabVIEW Development System [12] and its add-on Vision Development Module [13].

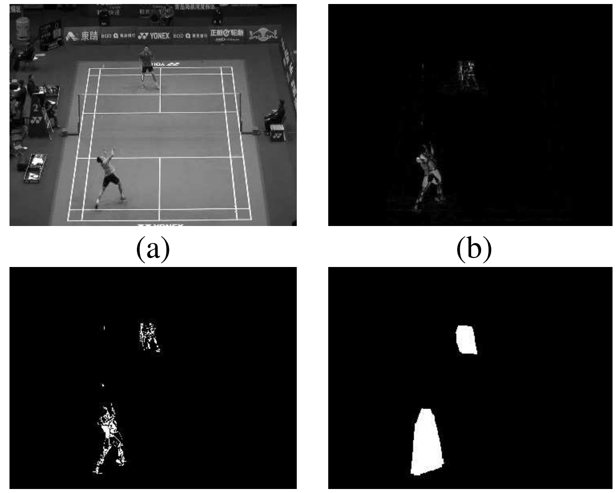
2.1. Automated data gathering

First, we aimed to automatically extract player position data of badminton players using video footage. The image processing algorithm developed in [22] was implemented for player position detection on the 2 dimensional plane of the badminton court floor. This position data was then annotated on nine tactically important cells on the badminton court using the annotation method and the optimal court cell borders identified in [22]. The trajectories of the players were extracted in the form of numerical strings.

The ability of the image processing algorithm to accurately detect player positions is evaluated in section 3.1.

2.1.1 Player position detection

The image processing algorithm for player position detection [22] was implemented to identify the badminton player position on every 3^{rd} frame of the video. First, the corners of the court lines were manually annotated on the first frame of the video. This information is used for the calibration of all subsequent frames and the extraction of the real-world player position. Each video frame was converted to grayscale by extracting the luminance frame (figure 1 (a)). The absolute difference between every 3^{rd} frame of the video allowed the extraction of pixels with motion (figure 1 (b)). The resulting image was converted to binary by thresholding at a grey value of 40, with all pixels above 40 normalised to 1 (white) and the remaining pixels to 0 (black) (figure 1 (c)). Several morphological functions available in the Vision Development Module [13] were utilised (closing with a 9×9 kernel, single 3×3 erosion and drawing the convex hull) to combine white pixels belonging to each player into two separate segments (figure 1 (d)). The position of the player was obtained by identifying the bottom most pixel of each player segment, on the same horizontal position as its centre of mass.



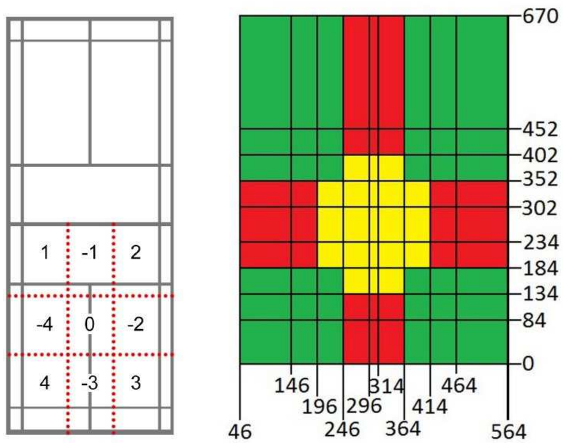
(a) (b) (c) (d)

Figure 1. Image processing. (a) Video frame converted to grayscale, (b) absolute difference of every 3^{rd} frame, (c) converted to binary image, (d) player segments following morphological operations [22].

2.1.2 Player position annotation

Each half of the badminton court was divided into nine tactically important cells (figure 2 (a)) as defined in [22]. The optimum borders of these tactical cells and the sub cells (figure 2 (b)) required for the annotation method were experimentally determined in [22].

The positions of badminton players were annotated on the tactical cells using the dynamic window annotation method [22]. In this method, the player position is first annotated on the sub cell and the respective main cell that corresponds to the player position on the first frame of the video. The dynamic window is a rectangular segment of 3×3 sub cells, centered on the current location (sub cell) of the player. For the player to be annotated onto a different sub cell and hence the respective main cell in the subsequent frames, the player must transition outside the dynamic window. This method prevents the player transitions being annotated as a result of small movements on the court or slight inaccuracies in the player position detection.



(a) (b)

Figure 2. Tactically important cells on a badminton court. (a) Each half of a badminton court divided to nine cells and labelled, (b) the optimal borders of the nine cells and sub cells for player position annotation [22].

2.1.3 Player trajectory extraction

The position data as the player transitions through the tactical cells can be considered trajectories and can be represented in the form of numerical strings, where the elements of the string represents the labels of each cell (figure 2 (a)) and the order of elements represent the order of transitions. For example, the following numerical string can be considered; 1 0 -4 0 -3 0 1.

2.2. Tactical movement extraction and classification

Next, we aimed to extract tactically important information from the trajectories which can then be illustrated in a manner that is easily comprehensible to a domain expert. Trajectories that occur frequently were identified, and ten distinct tactically important movement groups were defined. We propose a classification approach where the frequent trajectories were represented in vector space and classified to the ten tactical movement groups using an appropriate similarity measure.

The performance of the proposed classification approach is evaluated in section 3.2.

2.2.1 Frequent trajectory extraction

Badminton matches consist of variable length segments of play which are called rallies, starting at the service (the first shot) and ending when the shuttlecock hits the floor (end of rally). First, the trajectories of badminton players in the form of numerical strings were manually segmented into separate rallies, where the trajectories of each player during individual rallies were represented by separate numerical strings. Next, parts of the trajectories that occur repetitively in multiple rallies (contiguous elements common to multiple strings) were identified through the extraction of common substrings (CSS) [4].

However, a large quantity (hundreds or thousands) of frequent trajectories cannot be illustrated in a manner that is easily comprehensible, and hence, does not allow tactical planning or the development of counter tactics to defeat opponents. We aimed to group the frequent trajectories to a manageable number of groups, allowing the visualisation of a particular athletes' tactical tendencies.

2.2.2 Definition of tactical movement groups

For the purpose of our experiments we decided to group the frequent trajectories to ten tactical movement groups, each representing a distinct movement on a badminton court (figure 3). These groups were defined following discussions with domain experts (tactical analysts and coaches of the National Sports Institute of Malaysia). Four groups from the centre 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). The frequent trajectories could be classified to these ten groups and the results used to visualise meaningful tactical data.

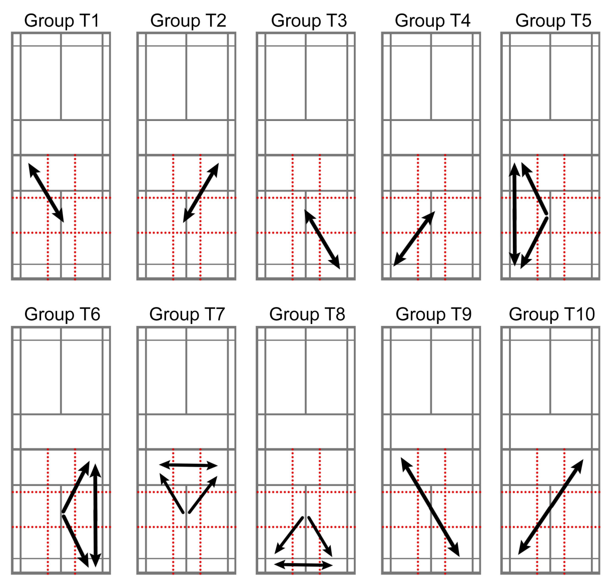


Figure 3. Ten tactical movement groups on a badminton court.

2.2.3 Proposed classification approach

We aimed to use the k-Nearest Neighbour (k-NN) classification algorithm [2] where an appropriate similarity measure for the frequent trajectories must be identified. The frequent trajectories while represented as numerical strings are of variable lengths and this property must be considered when evaluating similarities between strings. However, the frequent trajectories of player moving on the tactical cellular space of a badminton court could also be represented in vector space.

Consider a trajectory X, in cellular space, where X can be represented according to the tactical cells as $(C_1, C_2, , C_n)$, where n is the number of cells, and C_n is the number of times the trajectory intersects the n^{th} cell. The trajectory is effectively represented by an n-dimensional vector.

$$X = (C_1, C_2, ..., C_n) \tag{1}$$

For our case on a badminton court (figure 2 (a)) with nine cells (n = 9), each trajectory was represented as a 9 dimensional vector.

$$X = (C_1, C_2, ..., C_9) \tag{2}$$

we represented all frequent trajectories in vector space, and cosine similarity (CS) [14] was used as the similarity between vectors for classification. The cosine similarity between two frequent trajectories represented as vectors (X_A and X_B) is defined as follows;

$$X_A = (C_{A1}, C_{A2}, ..., C_{A9}) \tag{3}$$

$$X_B = (C_{B1}, C_{B2}, ..., C_{B9}) \tag{4}$$

$$CS(X_A, X_B) = \frac{\sum_{i=1}^{9} C_{Ai} C_{Bi}}{\sqrt{\sum_{i=1}^{9} {C_{Ai}}^2} \sqrt{\sum_{i=1}^{9} {C_{Bi}}^2}} \tag{5}$$

3. Experiments and results

3.1. Validation of player position detection

The accuracy of the player position detection was validated against manual annotation of video footage by a human domain expert (tactical analyst from the National Sports Institute of Malaysia).

Video footage from international badminton tournaments of the highest level (Badminton World Federations Super Series Tour, the Badminton World Championships and Olympic Games) captured by a competing team were used in this validation. One match from each tournament was chosen at random from the latter stages of the tournament (quarter finals, semi-finals, finals) ensuring the level of competition was high. In badminton, the play consists of segments called sets, where the set ends when a player reaches 21 points. At the end of the set the players change playing sides on the badminton court. At least ten rallies were chosen from each match on two sets (at least five rallies per set), to ensure situations with both players on each half of the court were considered. The chosen rallies were from the middle of the set after the players reached five points in each set.

The mid-point between the two furthest limbs of the player in contact with the ground was considered as the position of the player for the manual annotation. The automated player position detection was compared against the manual annotation, and if the error was less than 50 cm, the automated detection was considered correct.

The automated player position detection was evaluated according to the top and bottom halves of the badminton court (tables 1 and 2). The accuracy ranges from 94.59% to 98.34% depending on the tournament and the location of the court. The average accuracy is 96.03% and 97.09% for the top and bottom halves respectively. Note that SS indicates Super Series level tournaments and MS indicates multi-sport events. The Worlds Championships is rated higher than the Super Series, and is the largest event organized by the Badminton World Federation.

Tournament	Total frames	Correctly detected	Accuracy
All England Open(SS)	183	177	96.72%
China Open(SS)	241	237	98.34%
Malaysia Open(SS)	247	236	95.55%
World Championships	580	555	95.69%
Olympic games(MS)	259	245	94.59%
Total	**1510**	**1450**	**96.03%**

Table 1. Accuracy of automated player position detection on the top half of the badminton court.

Tournament	Total frames	Correctly detected	Accuracy
All England Open(SS)	183	179	97.81%
China Open(SS)	241	235	97.51%
Malaysia Open(SS)	247	236	95.55%
World Championships	580	567	97.76%
Olympic games(MS)	259	249	96.14%
Total	**1510**	**1466**	**97.09%**

Table 2. Accuracy of automated player position detection on the bottom half of the badminton court.

3.2. Evaluation of k-NN classification

For our classification experiments, we use a data set of 2038 frequent trajectories extracted from 10 international badminton matches using the methods described in sections 2.1 and 2.2.1. The ten badminton matches were chosen at random from the video library of the National Sports Institute of Malaysia and the 2038 frequent trajectories represent all the frequent trajectories extracted from these matches. Each trajectory was annotated as belonging to the tactical movement groups (T1 to T10) or as undefined by a domain expert (tactical analyst of the National Sports Institute of Malaysia). This annotation acts as the class label for each trajectory. 10-fold cross validation [7, 16] and the performance measures accuracy, precision, recall, and F-score [19] were used for the evaluation.

First, we aimed to determine the optimum value of k. The classification was carried out with the neighborhood size (value of k) reduced from 9 to 1, where the smallest value of k with the highest performance was considered the optimal neighborhood. The highest performance (table 3) of 97.79% accuracy, 97.81% precision, 97.44% recall, and 97.62% F-score is achieved with a k value of 1(nearest neighbour).

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

Table 3. Performance of the k-NN classification of frequent trajectories, using cosine similarity as the similarity measure.

Next, we evaluated the performance of the classification to individual classes (groups T1 to T10 and undefined) with the optimum value of k (table 4). The per-class accuracy of the classification is high with 98.87% accuracy for the undefined class being the lowest. The accuracy for the classes T1 to T10 are substantially higher with the lowest being T9 at 99.31%. The performance of the classification to individual

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%

Table 4. Performance of the classification to individual classes when k=1.

classes T1 to T10 also have a high F-score, with the lowest for class T10 at 96.69%. The performance is the lowest for the undefined class where the precision, recall, and F-score are 93.81%, 86.89%, and 90.21% respectively.

4. Discussion

4.1. Accuracy of player position detection

The player position detection through image processing was implemented and evaluated using video footage captured at the highest level international tournaments. Due to the tedious nature of manual annotation, the number of frames required for evaluation was kept at a minimum while ensuring as much of the variable conditions were considered. Multiple matches from multiple tournaments were chosen. However, within each tournament, the lighting conditions do not change and as such only a few rallies (at least ten) were considered from one match at each tournament.

For this evaluation, automatic detections within 50 cm of the manual annotations were considered a correct detection. This lenient measure is possible when considering our application requirement, where the player position is to be annotated on tactically important cells (figure 2(a)). The width of the court cells (figure 2(b)) and the use of the dynamic window [22] allows such a lenient error margin.

At international badminton tournaments, a specific location is allocated for video capture by the host nation. This location is always behind the court at an elevated angle from ground level with the playing field in full view, similar to video footage of badminton on television broadcasts. The exact location is entirely dependent on the discretion of the host nation. As such, a systematic evaluation with video captured at varying angles and with players in various coloured clothing could not be conducted. However, the video footage used in our experiments accounts for the major tournament environments, and the results suggest that this method is applicable at such environments.

4.2. Performance of classification

Classification of the frequent trajectories (represented in 9-dimensional vector space), using cosine similarity as the similarity measure, had the highest performance when using the nearest neighbour to classify (k=1). The performance improved consistently when the neighbourhood was reduced by lowering the value of k. This is likely due to the small number of tactical cells on the badminton court, where trajectories belonging to different tactical movement groups may be similar when represented in vector space. In such a situation, a smaller neighbourhood would result in higher accuracy classification.

When looking at the results of the per-class classification at k=1, the classification to tactical movement groups T1 to T4 (movements to corner cells) was very good with only a few false positives and false negatives (7 in total for all four labels). This is reflected in the high F-score in table 4. The performance of the per-class classification is low for the undefined class. The 86.89% recall for this group is due to the high false negative rate, where trajectories that should be considered undefined were classified to other labels. This is clearly the largest deficiency in the classification approach.

4.3. Player profile generation

The tactics of a player in badminton causes his/her opponent to move around the court. As such, when evaluating the tactics of a player, the trajectories of his/her opponent is considered. The classified frequent trajectories (of opponents) can be illustrated in a visual manner as tactical profiles. Figure 4 (a) is the tactical profile of a male singles badminton player ranked within the world's top 20. This profile illustrates the frequent trajectories of left and right handed opponents of the badminton player, classified to the ten tactical movement groups (T1 to T10).

Based on the profile, there is a clear preference by this player to use tactics T3, T6, and T9, against left handed opponents. This indicates that this player moves his left handed opponents to cell 3, along the right side of the court between cells 2 and 3, and along the diagonal between cells 1 and 3. These three trajectories are illustrated in figure 4 (b) and clearly indicates a preference to base tactics using cell 3. Such knowledge can be easily used to predict opponent play and device counter tactics.

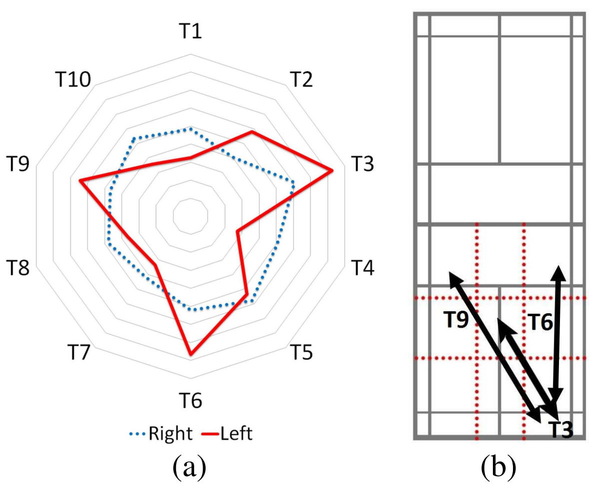


Figure 4. Visualisation of tactics. (a) Player tactical profile against left and right handed opponents, (b) tactical (movements on court) preferences against left handed opponents.

4.4. Applicability and shortcomings

When considering the final application to develop player tactical profiles, the lower performance of the classification to the undefined class should not hinder the visualisation as the profiles are based on the other groups. Additionally, the player profiles are not required to indicate specific numerical data, and instead a visual representation of tactical tendencies and a comparison of tactics against a collection of possibilities. As such, small inaccuracies could be tolerated without compromising the effectiveness of the profiles generated.

As explained previously [1, 8], sports tactical analysts often use cellular representations of sports fields, where each cell represents a tactically important space. It stands to reason that the proposed approach to classify trajectory data represented in cellular space may be applicable in other sports, where if needed, the cellular space could be expanded to a higher number of cells, and as a result a higher dimensional vector space.

The classification approach poses a challenge, in that it requires a training set of data to train a classifier. If the classes (tactical movement groups) require modification, a domain expert is required to perform the tedious task of recreating training data. A different approach, perhaps an unsupervised method for clustering where training data is not required could improve the efficiency of adaptation, resulting in a more flexible system.

4.5. Future work

When considering the work reported and possible improvements to the classification performance, modifications or enhancements of the similarity measure is worth considering. Rules based on the unique properties of the application such as the lengths of the frequent trajectories or the dimensions of the vector space may improve classification performance. Additionally, other similarity measures for vector space models may be considered and evaluated for their effectiveness when compared to the cosine similarity.

The frequent trajectories could be represented through alternative means instead of vector space, leading to alternative similarity measures for classification. An ideal starting point might be the representation as numerical strings used for the extraction of common substring in the reported work.

Finally, unsupervised models for clustering trajectories may lead to models capable of profiling player tactics without the need for training data, allowing the efficient generation of tactical profiles based on requests from coaches and athletes.

5. Conclusion

This work has successfully tackled a domain specific problem in developing an automated approach for badminton tactical analysis.

An image processing algorithm for automated player position detection was successfully implemented and validated using video footage captured at the highest level badminton tournaments, including the Olympic Games. The average accuracy of player position detection is 96.03% and 97.09% for the top and bottom halves of the badminton court respectively.

The player trajectories were represented as numerical strings, and frequent trajectories extracted by identifying common substring. The frequent trajectories were then represented in 9-dimensional vector space and classified using the k-NN algorithm with cosine similarity as the similarity measure. The classification performs at 97.79% accuracy, 97.81% precision, 97.44% recall, and 97.62% F-score, when k=1.

The classified frequent trajectories can be visualised as player tactical profiles. Such information can be used by coaches and athletes for developing counter tactics.

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