2014 13th International Conference on Control, Automation, Robotics & Vision
Marina Bay Sands, Singapore, 10-12th December 2014 (ICARCV 2014)

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Application of Computer Vision to Automate Notation for Tactical Analysis of Badminton

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***Abstract*— In tactical analysis of fast-paced net-based sports such as badminton, the identification of habits and movement of an opponent provides an advantage in terms of reaction time, which results in a player obtaining control of the game. A tactical analyst in badminton segments the court using imaginary lines, and intuitively notates the position of a player according to those segments throughout the game. This paper presents a computer vision based approach to automate this notational process. Motion tracking of the badminton players identifies their position throughout the game. Different court segmentation patterns are tested to identify the borders of the segments to match the intuitive segmentation performed by a badminton tactical analyst. By application of a dynamic window for assigning players to court segments, we achieve an accuracy level of above 85%.**

***Keywords*—Image processing, Badminton, Tactical analysis, Court segmentation, Automation**

I. INTRODUCTION

Tactical analysis is a key service provided to elite athletes, used to identify patterns of play and predict opponents' moves allowing a team or individual player to improve performance. A tactical analyst in badminton manually notates the movement of players and the types of shots played throughout the game of badminton, often resulting in large amounts of data to evaluate [1]. As the demands of elite sports and its commercialization increase through the years, much work has been carried out to apply technology to the services provided by the support staff increasing the efficiency and effectiveness [1],[2]. Analysis of the types of shots, the positions on the court they are executed from and the success rates form the basic framework of tactical analysis in badminton [3].

Efforts made in the area of unobtrusive computer based data gathering in sports have been through examination of video footage of the sport. Work related to tactical analysis concentrates on tracking the motion of a player, and/or the ball/shuttlecock [4]-[10]. Work on badminton specifically has been rare and most past research concentrates on tennis, where the playing area is larger and the tracked players rarely occlude each other as the play takes place at the baseline (top and bottom of the court region) [6]-[9]. Experimentation with tennis has allowed tracking the motion of players through occlusion [5], using multiple fixed cameras [8], and some tactical analysis through analysis of the motion of individual players through time [9].

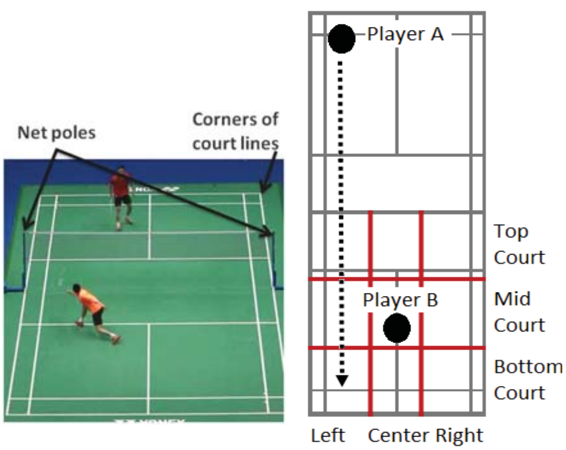
Research specifically on badminton motion tracking to detect the movement of players and the shuttlecock at amateur level in a training environment from a fixed camera position is interesting [4]. However, the fixed conditions assumed at training venues and the camera angles are not similar to elite competition venues. Detecting the playing region and the start of the play (service) is very helpful in the automation of examining a badminton video as the movements and events are analyzed during the playing segment (following service) of the video [10]. The definition of the service could cause errors as it is similar to events that could occur during the play, which may explain the low level of accuracy in detecting the event.

Research in automated tracking in sports concentrates on the accuracy of tracking. However work on tactical analysis or playing patterns of sport tend to divide the playing area into segments [2],[3],[11].The accuracy of the player position is not required to be exact, and rather the percentage of the play from a segment or the frequencies of events occurring at a particular segment are examined. This is because tactical analysis in its nature attempts to predict the play of an opponent. This prediction does not need pinpoint accuracy. In Fig.1(b) if it is known that player A would execute a straight shot as indicated by the arrow, player B would be prepared in advance to move in that direction and may initiate the movement prior to player A making contact with the shuttlecock. However, player B only requires knowing the general direction of the shot to initiate his/her movement in that direction and knowledge of the shot to pin point accuracy would be redundant.

Tactical analysis in sports is said to be objective. However, at present, there is some subjectivity involved, which is accepted by the coaches as a requirement of the analysis. In a game of singles badminton, each half of the court is divided into 9 segments (Fig.1(b)) which the player occupies as he/she moves around the court. Boundaries of these segments are imaginary and an analyst intuitively notates the position of the player with respect to these segments during the game. A player moving (Fig.1(a)) from the mid court segments and lunging towards the top-left segment may be notated in the top-left segment by an analyst while being tracked and assigned on the mid-left segment by a computer.

In the literature, work on motion tracking has not been combined in any attempt to automate the subjective notational process carried out by a tactical analyst. This paper discusses an approach to automate this notational process providing a basis for automated tactical analysis in badminton. We track badminton players utilizing video footage captured at various elite level international badminton competitions by tactical analysts from the National Sports Institute of Malaysia. This tracked data is used to assign players to court segments, and various court segmentation methods (segment borders and shapes) are tested. We attempt to identify quantifiable borders for the segments, so that the automated assignments of players to segments simulate the subjective notational process of a tactical analyst.

The remainder of this paper is organized as follows. The methodology of tracking multiple badminton players and experimentation on segmenting the court is explained in Section II. Implementation of the court segmentation and results are discussed in Section III, with a discussion of results on each segmentation method and their strengths and weaknesses. Section IV discusses the comparison of the most accurate segmentation methods with respect to the subjective manual notational data. Finally, in section V we conclude the paper and discuss briefly on our future work.



(a) (b)

Figure 1. (a) View of badminton court as per video footage, (b) Top view of badminton court.

II. METHODOLOGY

Two important steps in the process are the tracking of badminton players to identify their position and assigning this position to court segments. The tracking of badminton players was validated only through visual inspection as pinpoint accuracy was not needed. Experimentation with different segmentation methods was conducted to ensure the combined process simulates the manual notation process. The process of identifying the player position and assigning the player to court segments is depicted in Fig.2.

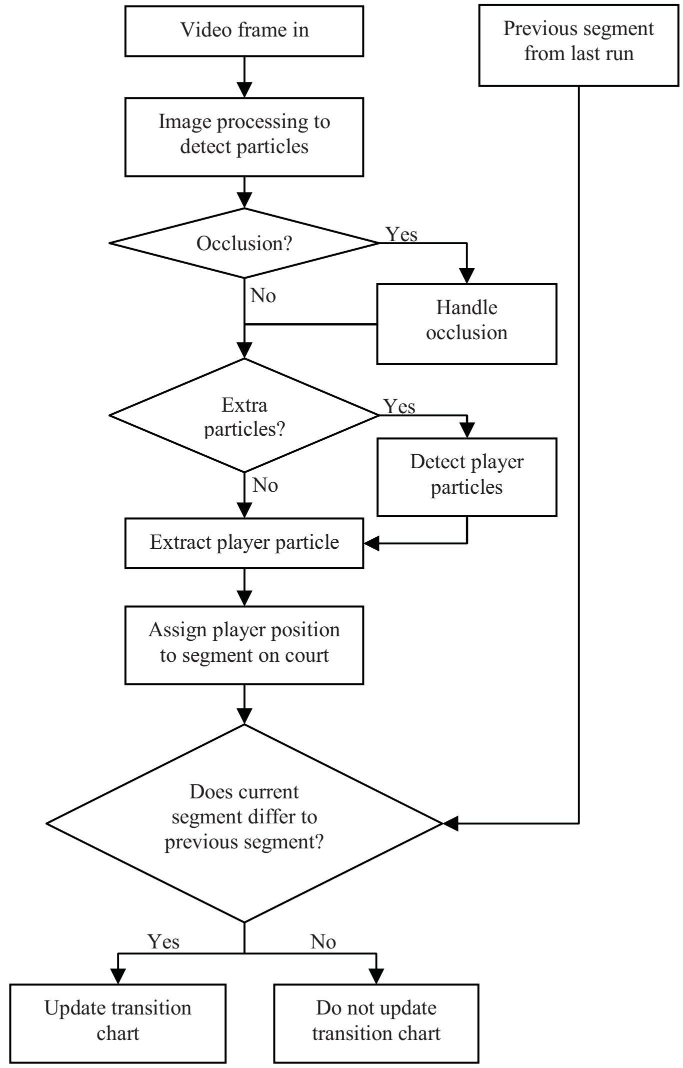


Figure 2. Methadology flow of tracking badminton players to identify transitions to differnt segments of the court.

A. *Tracking of Badminton Players*

Tracking of badminton players within the scope of this research includes several constraints and challenges, and this application is expected to function under these constraints. Badminton tournaments at the elite level have restrictions on video recording. Video recording for a national team is allowed from a location set by the host country. Hence, the camera position cannot be fixed. The camera is positioned at the rear of the court and the view is an elevated view as shown in Fig.1(a). The angle of elevation and lateral position are not fixed. The cameras are operated by tactical analysts, coaches or non playing members of the team who are not experts in operations such as proper leveling or disabling the auto focus function of these cameras. Some constraints such as the court surface having a standard green color and the camera always being positioned at the rear of the court with the playing area in full, unobstructed view are advantageous.

The process of tracking the players consists of several major steps where image processing algorithms are used. The parameters for these algorithms are chosen by inspecting common values and the effect on the output. First the corners of the court lines and the bottom points of the net poles depicted in Fig.1(a) are manually notated at the start and this data is used to extract the playing region to remove the background of the image. Then as in Fig.3(a), the luminance frame of the image is extracted to obtain a grayscale image. The motion is detected in every 3rd frame of the video by finding the absolute difference of the grayscale value compared to the last frame the motion was obtained in. The resultant image is noisy due to the unstable lighting conditions and the autofocus feature in the camera (Fig.3(b)). The grayscale values of the noisy pixels tend to fall on the lower end of the scale as the value difference in every 3rd frame caused by lighting and auto focusing is small. The grayscale threshold value of 40 was chosen after examining video footage from all the Badminton World Federation Super Series events. In Fig.3(c), pixels of grayscale value above 40 are extracted to convert the image to a binary image. Finally morphological operations (closing with a 9×9 kernel, single 3×3 erosion and drawing the convex hull) combines the particles belonging to the same player into one particle (Fig.3(d)).

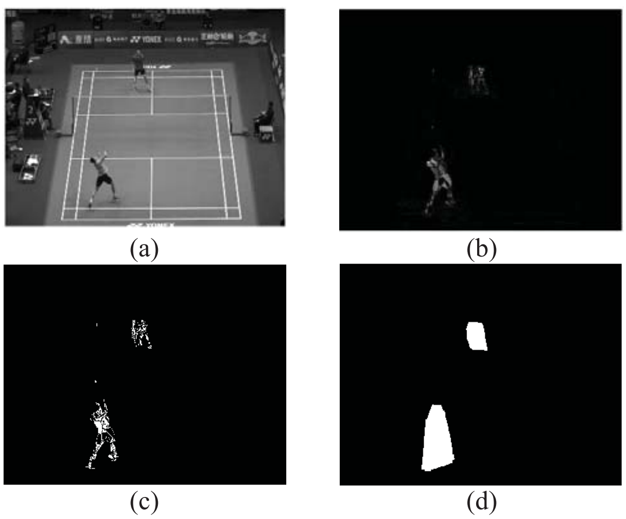


Figure 3. (a) Grayscale image after luminance frame extraction, (b) Absolute difference of every 3rd frame, (c) Binary image following grayscale threshold, (d) Particles following morphological operations.

On some occasions, three or more particles are detected. This is due to the shuttlecock or the head of the racket being detected away from the player as a separate particle. These particles however are very small comparative to the player particle and this situation is dealt with by selecting the largest particle within the bounding box of the previous frames and disregarding all other particles.

In situations where both players are close to the net, as in Fig.4(a), occlusion takes place and thus only one particle is detected. In such situations the bounding boxes of the previous frame are superimposed on the particle (Fig.4(b)). In Fig4(c), the segment of the particle falling within the respective bounding boxes are considered as the two separate player particles.

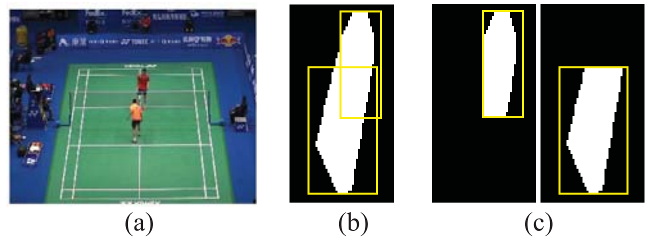


Figure 4. (a) Occlusion of two players near the net, (b) One particle detected, (c) Particle segment within the bounding box separated.

The bottom pixel of the particle, on the vertical line through the center of mass of the particle is identified as the position of the player on court. Perspective calibration is carried out on this position value using the data on the corners of the court lines and the bottom of the net poles.

B. *Segmentation of Court*

For the purpose of these experiments the court segments are labeled as shown in Fig.5(a). Note the center segment labeled 0, corners positive and the remaining segments negative. Center court segment is considered the neutral position in singles badminton. A player plays a shot at a segment and returns to the neutral position to prepare for the next shot. The positive segments (corners) are accepted as the advantageous positions on a court to send an opponent to as it results in them having to move further between shots. The negative positions are considered less advantageous. This labeling method allows us to plot the transitions of the player in Fig.5(b), where both positive and negative transitions can be identified visually at a glance. The transition of the player from one court segment to another is plotted against the transition number.

Different court segmentation methods are tested and compared against a manually notated ground truth sample (Fig.5(b)). Note the number of transitions in the ground truth sample and the number of transitions to negative segments. These two parameters allow us to identify test results, to be discarded without further scrutiny as they are not close to the ground truth sample. For the purpose of this paper, the movement of the player on the bottom half of the court through one game is used to illustrate the sequential transition pattern. For the most accurate segmentation methods, data with respect to both players on court are discussed in section IV.

III. IMPLEMENTATION AND RESULTS

A. *Simple Segmentation*

In this methodology the court is segmented into 9 and labeled as in the court segmentation for manual notation although the sizes are not equal to those segments in Fig.5(a). The transitions of the player from segment to segment are followed through the playing portions of a badminton game.

1) *Experiment 1*

The court segment borders are chosen by carefully observing the tracked position of players as they move from the center (0) segment to the sides and the top and bottom segments. The width of the left (1, -4 and 4) and right (2, -2 and 3) side segments is 150 centimeters. The height of the bottom (3, -3 and 4) and the top (1, -1 and 2) segments are 134 and 268 centimeters respectively as shown in Fig.6(a).

The results in Fig.6(b) show a large number of transitions to negative segments when compared to the ground truth sample in Fig.5(b). As there are no common side boundaries between the center segment and positive segments, a player moving from center to a corner or vice versa finds it difficult to move without first transitioning on to a negative segment. The only possibility is to move via a path exactly through the adjoining corner or at an invisible speed.

2) Experiment 2

In Fig.7(a) the negative segments are altered to allow the center and positive segments to have common side boundaries. The center segment is retained at the same size.

The results in Fig.7(b), shows a larger number of transitions when compared to the ground truth sample in Fig.5(b). The results also show quick repeated transitions back and forth between adjacent segments, which are due to the tracked position of the player alternating between segments while located at the border of a segment.

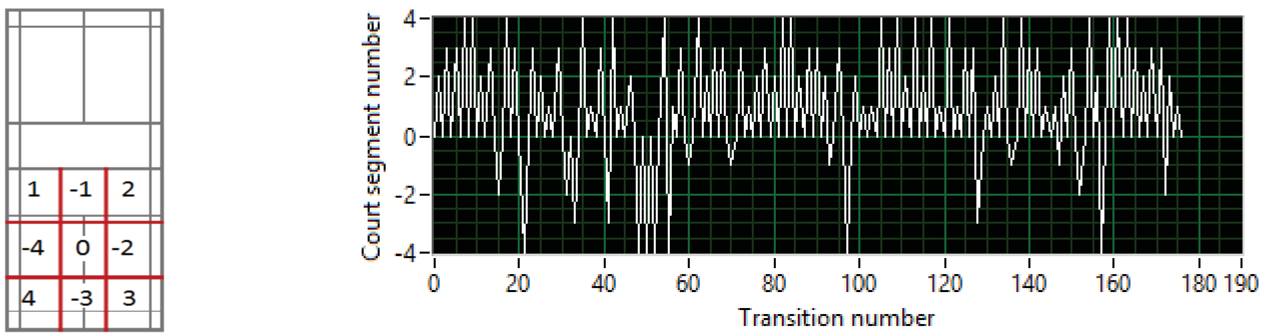


Figure 5. Ground truth sample: (a) Segmentation of the bottom half of a badminton court and segment numbering , (b) Ground truth sequential transition pattern of player on bottom half of court as notated by a tactical analyst.

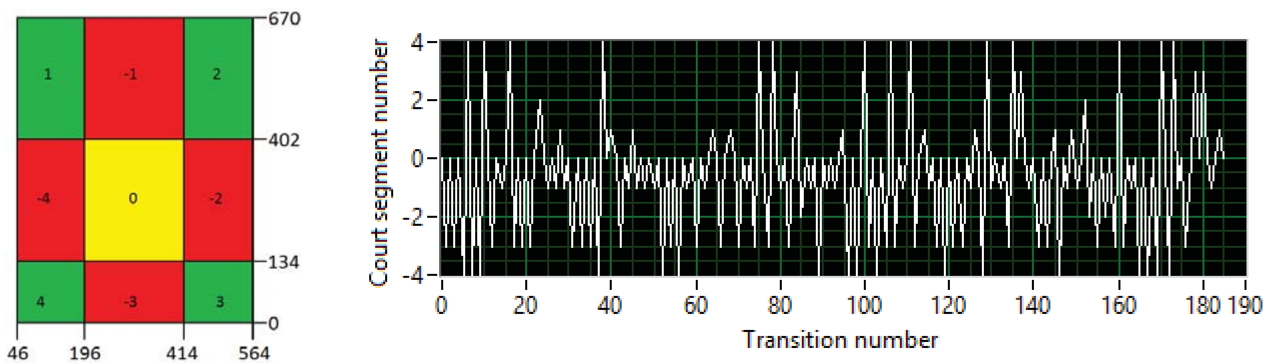


Figure 6. Experiment 1: (a) Segment borders for bottom half of a badminton court and segment numbering , (b) Experimental sequential transition.

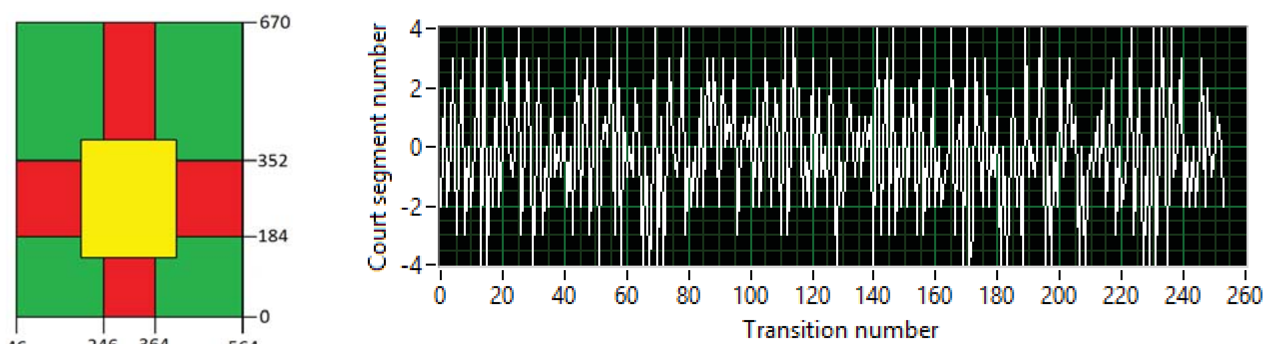
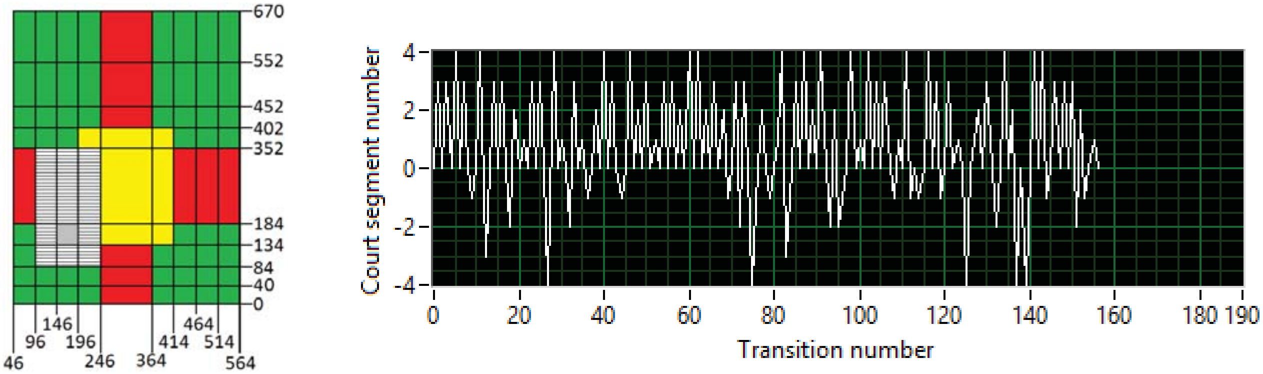
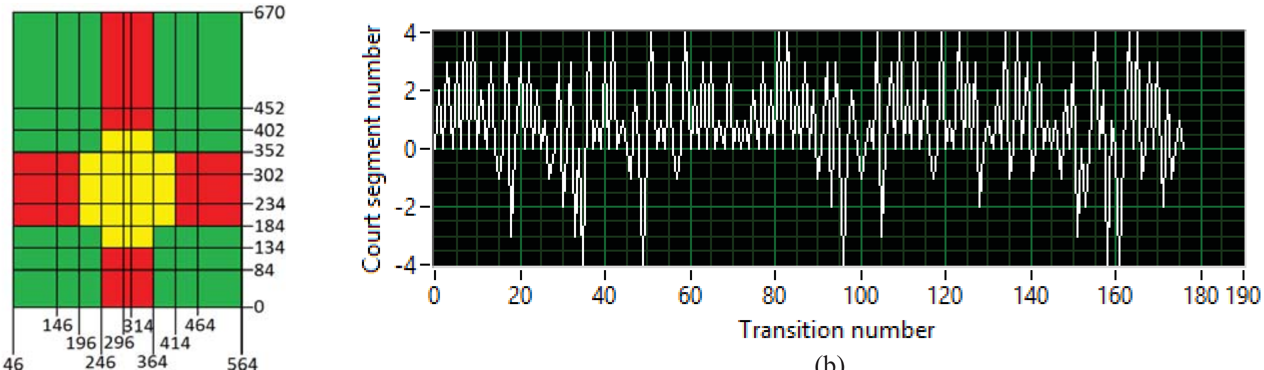


Figure 7. Experiment 2: (a) Segment borders for bottom half of a badminton court, (b) Experimental sequential transition.



(a) (b)

Figure 8. Experiment 3: (a) Segment and sub segment borders for bottom half of a badminton court with dynamic window illustrated in stripes and center of dynamic window in dots, (b) Experimental sequential transition.



(a) (b)

Figure 9. Experiment 4: (a) Segment and sub segment borders for bottom half of a badminton court, (b) Experimental sequential transition.

B. Segmentation With a Dynamic Window

In this methodology, the court segments are further divided into sub segments and a dynamic window (of size 3×3 sub segments) is introduced (Fig.8(a)). The player position is assigned to a sub segment and to the respective main segment. The dynamic window is centered on the sub segment occupied by the player. The player is reassigned to a different sub segment and hence a different main segment, only if he/she transitions outside the dynamic window. The dynamic window effectively extends the segment currently occupied by the player to the adjacent segments.

1) Experiment 3

In Fig.8(a), the court segments from experiment 2 are further sub divided and the dynamic window illustrated.

The results in Fig.8(b), show fewer transitions to negative segments and no back and forth movement between adjacent segments. However, this method has an inherent flaw where the movement from a positive segment to a negative segment becomes unlikely as the dynamic window extends the positive segment to the negative segment, which only has three sub segments.

2) Experiment 4

The segmentation from experiment 3 is altered as shown in Fig.9(a). The negative segments are further divided into six sub segments limiting the expansion of positive segments to an adjacent negative segment. The corner sub segments of the center segment from Fig.8(a) are assigned to the respective positive segments.

The results in Fig.9(b) shows encouraging results compared to the ground truth sample in Fig.5(b).

IV. RESULTS & DISCUSSION

Experiment 1 shows too many transitions to negative segments and experiment 2 has a high transition number compared to the ground truth sample in Fig.5(b). These results are discarded. In table I and II, the sequential transition patterns for both players on court (top and bottom half players) from experiments 3 and 4 are compared against the ground truth samples for each player.

TABLE I. TRANSITION OF PLAYER ON BOTTOM HALF OF THE COURT

	Extra	Missing	Incorrect	Accuracy
Experiment 3	18	38	5	75.71%
Experiment 4	19	19	4	87.01%

TABLE II. TRANSITION OF PLAYER ON TOP HALF OF THE COURT

	Extra	Missing	Incorrect	Accuracy
Experiment 3	9	54	6	65.52%
Experiment 4	20	15	3	89.66%

The accuracy of the experimental transition patterns is the number of correctly registered sequential transitions with respect to the sequential transition pattern in the ground truth sample. The objective is to identify a segmentation method with a high percentage of accuracy. There are three types of errors in the experiment results when compared to the respective ground truth samples.

Transitions identified by the experiments that are not notated by the analyst are considered extra samples. In badminton singles, a player typically moves from the center to a positive or negative segment to play a shot and then returns to the center. The extra transitions detected are mainly due to the tracked player transitioning on to an adjacent segment before returning to the center. This typically follows a particularly difficult shot, or playing a shot off balance resulting in irregular stepping patterns (footwork) by the said player where the tactical analyst would not consider the extra transition.

Transitions not identified by the experiments are considered missing samples. Missed samples tend to be a result of the subjective notation by the analyst of the player moving to the edge of the center segment and reaching for the shuttle in an adjacent segment. This situation is not registered by the computer as a transition while it is registered by the analyst. It should be noted that in most such cases two missed samples are registered together as the computer continued to register the player on the center segment while the analyst registered two transitions, both from the center to another segment and back to the center. We aim to simulate this subjectivity and hence to reduce the number of missing samples.

Incorrectly identified samples occur where the transition to a segment is identified by the computer, although it is assigned to the incorrect segment. Assigning player position to an incorrect segment occurs when the segmentation borders are incorrect. We aim to identify a segmentation method (segment borders) to simulate the subjective notation, hence the number of incorrectly detected transitions are to be minimized.

The lower number of missing samples and the higher accuracy level achieved in experiment 4 suggests that the court segmentation used in experiment 4 is the superior segmentation method of the segmentation methods tested.

V. CONCLUSION AND FUTURE WORK

We have successfully implemented a computer vision based methodology for tracking badminton players from video footage captured at elite level competitions. The position data was used to experiment on different segmentation patterns of a badminton court, in order to automate the subjective manual notation by a tactical analyst. Results show that simple segmentation of a badminton court cannot successfully simulate the subjective notation. The implementation of a dynamic window successfully reduces the repeated transitions between adjacent segments. Combination of the dynamic window and the segmentation with larger positive segments, proved to be the most accurate segmentation method with an accuracy of 89.66% and 87.01% for the top and bottom halves of the court respectively.

Further experimentation is required on the segmentation section with video footage from different tournament environments with varying camera angles. Experimentation on fine-tuning the sub segment sizes to alter the size of the dynamic window, and experimentation with dynamic segment borders depending on the current position of the player could possibly reduce the number of missing transitions and increase the percentage of accuracy. This is the first step on automating the tactical analysis carried out manually by tactical analysts in badminton.

ACKNOWLEDGMENT

The authors would like to express their gratitude to the National Sports Institute of Malaysia for partial sponsorship of this research and providing access to their video library.

REFERENCES

[1] A. Lees, "Science and the major racket sports: a review," *J. Sports Sci.*, vol. 21, no. 9, pp. 707–732, Sep. 2003.

[2] M. Hughes, M. T. Hughes, and H. Behan, "The evolution of computerised notational analysis through the example of racket sports," *Int. J. Sport. Sci. Eng.*, vol. 1, no. 1, pp. 3–28, 2007.

[3] K. T. Lee, W. Xie, and K. C. Teh, "Notational analysis of international badminton competitions," in *XXIII international Symposium on Biomechanics in Sports*, 2005, pp. 387–390.

[4] C. Bingqi and W. Zhiqiang, "A statistical method for analysis of technical data of a badminton match based on 2-D seriate images," *Tsinghua Sci. Technol.*, vol. 12, no. 5, pp. 594–601, 2007.

[5] J. Han, D. Farin, and P. H. N. de With, "Broadcast court-net sports video analysis using fast 3-D camera modeling," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 18, no. 11, pp. 1628–1638, Nov. 2008.

[6] D. Zhong and S.-F. Chang, "Real-time view recognition and event detection for sports video," *J. Vis. Commun. Image Represent.*, vol. 15, no. 3, pp. 330–347, Sep. 2004.

[7] J. Han, D. Farin, P. H. N. De With, S. Member, and W. Lao, "Real-time video content analysis tool for consumer media storage system," *IEEE Trans. Consum. Electron.*, vol. 52, no. 3, pp. 870–878, 2006.

[8] D. Connaghan, K. Moran, and N. E. O'Connor, "An automatic visual analysis system for tennis," *Proceedings. Part P J. Sport. Eng. Technol.*, pp. 1–16, Feb. 2013.

[9] W.-T. Chu and W.-H. Tsai, "Modeling spatiotemporal relationships between moving objects for event tactics analysis in tennis videos," *Multimed. Tools Appl.*, vol. 50, no. 1, pp. 149–171, Sep. 2009.

[10] S. L. Teng and R. Paramesran, "Detection of service activity in a badminton game," in *TENCON 2011 - 2011 IEEE Region 10 Conference*, 2011, no. rule 3, pp. 312–315.

A. Borrie, G. K. Jonsson, and M. S. Magnusson, "Temporal pattern analysis and its applicability in sport: an explanation and exemplar data," *J. Sports Sci.*, vol. 20, no. 10, pp. 845–852, Oct. 2002.