TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 14/19 pp594-601
Volume 12, Number 5, October 2007

A Statistical Method for Analysis of Technical Data of a Badminton Match Based on 2-D Seriate Images

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Abstract: The use of computer vision technology to collect and analyze statistics during badminton matches or training sessions can be expected to provide valuable information to help coaches to determine which tactics should be used by a player in a given game or to improve the player's tactical training. A method based on 2-D seriate images by which statistical data of a badminton match can be obtained is presented. Image capture and analysis were performed synchronously using a multithreading technique. The regions of movement in the images were detected using a temporal difference method, and the trajectories of the movement regions were analyzed using seriate images. The shuttlecock trajectory was extracted from all detected trajectories using various characteristic parameters. The stroke type was determined by comparing the shuttlecock trajectory data with a set of stroke definition data. The algorithm was tested at a training center, and the results were compared with baseline data obtained by expert visual inspection using four video samples, which included approximately 10 000 frames. The shuttlecock trajectory and stroke type were detected correctly in almost 100% of the analyzed video sequences. The average speed of the automated analysis was approximately 40 frames/s, indicating that the method can be used for real-time analysis during a badminton match. The system is convenient for use by a sports coach.

Key words: machine vision; 2-D measurement; badminton match; trajectory tracking; stroke type statistic

Introduction

At present, plays and goals in sporting matches are usually judged by the human eye, and recording is performed "manually" by human operators. With the recent improvement of computer hardware and technology related to image processing, computer vision is increasingly expected to replace manual operations in sports matches and training.

Several studies have been performed to analyze the movement of players and the ball in sporting events, and many developments have been made in the past few years. Pingali et al. developed a multi-camera real-time tracking system for sports broadcast applications and proposed techniques for the game of tennis for tracking the ball and players on video images obtained from stationary cameras[1,2]. Yu et al. proposed a framework to determine the location of a ball by looking for and analyzing the ball trajectory from broadcast soccer match video data[3-6]. Ekin et al. provided a framework for automatically analyzing and obtaining statistics of a soccer match in real-time[7]. Utsumi et al. proposed a detection and tracking method in order to detect and track the objects necessary to describe a soccer match[8]. Perš and Kovacic developed a multiple-camera-based player tracking system that could be used for simultaneously tracking several players in a large section of a handball court using a series of 384×288 pixels images acquired by fixed cameras[9,10]. Figueroa et al. considered the problem of tracking

Received: 2006-03-09; revised: 2006-12-04
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players during a soccer game through the use of multiple cameras[11]. Ye et al. have proposed a method for athlete identification by combining the segmentation, tracking, and recognition procedures into a coarse-to-fine scheme for jersey number (digital characters on the sport shirt) detection[12]. Wang et al. proposed an automatic technique for extracting color models of the playing surface and the team uniforms that can be used in higher-level processes such as tracking and recognition[13]. Qi et al. presented a framework for tracking sports players in videos recorded by static domestic cameras[14]. Zaveri et al. proposed an algorithm for detection and tracking of small and fast moving objects, such as a pingpong or a cricket ball, in sports video sequences[15].

In badminton matches and in training, in order to select the tactics required to deal with different opponents, the coach must have a good statistical knowledge of the tactics of the player. The ultimate goal of this study was to develop a system capable of real-time statistical analysis of data collected either during training or match-play, to provide information to assist training and to select match tactics.

The use of 3-D information should be able to provide accurate statistical data for analysis of a badminton match. However, obtaining 3-D information requires the use of more than two cameras, and real-time analysis requires high-capacity processors, the size and volume of which are generally too large for a practical implementation. Therefore, 3-D detection is not suitable for badminton coaches, as the equipment must be readily, transportable to remote match locations. In the present study, therefore, we develop a 2-D measurement and analysis system, which requires only one camera and a laptop personal computer.

1 Method

The system can be broken into a number of steps as follows.

(1) Capture of 2-D images of the badminton court that are suitable for use in measuring the shuttlecock trajectory using one camera.

(2) Extraction of moving objects from 2-D seriate images.

(3) Classification of moving objects and connection of their tracks.

(4) Extraction of the shuttlecock trajectory from entire tracks.

(5) Calculation of the statistics for the stroke type by comparing the characteristics of the detected shuttlecock trajectory and the definition of the stroke type.

1.1 Equipment

A Basler A601f series progressive scan CMOS (complementary metal-oxide-semiconductor transistor) camera was used to acquire sample images. The camera was designed for industrial applications. The primary features of the camera are as follows. The camera matches the 1394 TA (transmission adapter) digital camera specification. The maximal frame rate at full resolution is 60 frames/s. The asynchronous full frame is shuttered electronically. The camera has square pixels, and the frame size is 659×493 pixels. The camera was used to capture monochrome images.

Capturing and processing of each image were performed using a notebook personal computer with a Pentium 2.4-GHz CPU. The algorithm was developed based on the platform of a 2-D moving image measurement system, which was provided by Beijing Modern Fubo Technology Ltd., implemented using Microsoft Visual C++ 6.0.

1.2 Sampling a moving shuttlecock

1.2.1 Preparation for the sampling program

The application for synchronous capture, analysis, and data storage uses Windows multithreading technology. When the application is started, the captured thread is started and captured images are displayed on the screen. Then, when analysis and/or saving has begun, thread analysis and/or saving is started, and image analysis and/or saving is carried out synchronously.

1.2.2 Establishing the camera and demarcating the badminton court

In the present study we attempt to develop a real-time measurement algorithm for a moving shuttlecock in an actual match. Therefore, the image samples used in the present study should simulate scenes of an actual match as closely as possible. In order to capture the entire scene of the badminton court, the camera was mounted 5 m from the corner of the court at a height of 4 m from the ground and at an angle of approximately 45° from the vertical.

Before the image analysis, eight characteristic coordinates of the badminton court were selected manually, as shown in Fig. 1. The representational points comprise the two top ends of the badminton net (point 1,3), the two feet of the net frame (point 2,4), and the four corners of the court near the net (point 5-8).

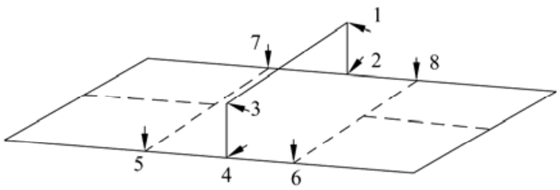


Fig. 1 Representational points of the net and the field

1.3 Trajectory tracking and analysis

1.3.1 Concept of direction number

In the present study we introduce the concept of a direction number, which is used to determine the flight direction and stroke type. The direction number is defined as follows. When the x coordinate of a point on the trajectory is increased relative to previous point, the direction number is positive. When the x coordinate of a point on the trajectory is decreased relative to previous point, the direction number is negative. The application states that the initial direction number is zero. When tracking is complete, the application can determine the direction and length of the trajectory according to the value of the direction number.

1.3.2 Object detection

Detection of differences between current images and the background is the most common method used for detection of the moving area in image processing. However, this method requires a background image in which there are no moving objects, which is difficult to obtain in a match environment. In the present study we therefore detect the moving area using the difference between two consecutive frames in the seriate data. This detection method is hereinafter referred to as the temporal difference method. The temporal difference method includes the following procedures. First, the original image is defined as

$$X^t = \{x^t_{(i,j)} | 0 \leqslant i < M; 0 \leqslant j < N|\} \tag{1}$$

where M is the width of the image and N is the height of the image.

Second, the temporal difference image is defined as

$$R^t = \begin{cases} 255, & X^t - X^{t-1} > n; \\ 0, & X^t - X^{t-1} < n \end{cases} \tag{2}$$

where n is a threshold that can be modified and R^t is a binary image.

The outline of each white pixel block is measured on the binary image. According to the coordinates of the outline, the barycenter of each white pixel block is calculated as

$$X = \frac{1}{n}\sum_{i=0}^{n-1} x_i, \qquad Y = \frac{1}{n}\sum_{i=0}^{n-1} y_i \tag{3}$$

where X is the x coordinate of the barycenter, Y is the y coordinate of the barycenter, x_i and y_i are the x and y coordinates of point i on the outline, and n is the number of points on the outline.

1.3.3 Trajectory detection

(1) Establishing the trajectory record

The trajectory record for each frame includes the following information:

(a) The coordinates of the trajectory in the current scene;

(b) The angle between the x-axis and the line connecting the current point with the previous point on the trajectory;

(c) The distance between the current point and the previous point on the trajectory;

(d) The current direction number.

(2) Trajectory matching

$C^i_m(x,y)$ is used to describe the barycenter coordinate of area i in frame m. The distance L and the angle A from $C^i_m(x,y)$ to $C^{\max}_{m-1}(x,y)$, which is a point belonging to the longest trajectory in the m−1 frame, are calculated. If the distance L is between the established longest and shortest distances, and the angle A is between the established largest and smallest angles, then $C^i_m(x,y)$ is judged to be a point on the longest trajectory. The point $C^i_m(x,y)$ is then recorded in the longest trajectory record and the direction number of the longest trajectory is modified. If $C^i_m(x,y)$ is judged not to belong to the longest trajectory, and if $C^i_m(x,y)$ is matched another trajectory, it is recorded as belonging to the matching trajectory record. If $C^i_m(x,y)$ does not match any trajectory on the m−1 frame, then a new trajectory record starting at $C^i_m(x,y)$ is created.

In the trajectory matching, several points on the same frame may appear to match the same trajectory. In this case, the point nearest to the trajectory is recorded as belonging to the trajectory.

If none of the barycenters on frame m matches any of the barycenters on frame m−1, then the longest trajectory up to this point is analyzed in order to determine whether the longest trajectory is the shuttlecock trajectory.

1.4 Detecting the shuttlecock track

$T_{\max}$ denotes the longest trajectory among all of the trajectories, and $\lambda_1, \lambda_2, ..., \lambda_m$ denote all of the properties that are used to evaluate whether a trajectory is the shuttlecock trajectory. These properties include the trajectory length, the trajectory camber, and the trajectory direction number. The reliability parameter $\psi(T_{\max})$ of the shuttlecock trajectory is defined as

$$\psi(T_{\max}) = \sum_{i}^{m} \psi_i(\lambda_i) \tag{4}$$

If the reliability is greater than some established threshold, the trajectory is judged to be the shuttlecock trajectory. The shuttlecock trajectory is then analyzed to determine the stroke type. If the stroke type is determined, all of the trajectory records are deleted, and the detection process is restarted. If the longest trajectory is not the shuttlecock trajectory, all of the trajectory record is stored in memory and the detection process is restarted.

During the detection process the shuttlecock may temporarily leave and then reenter the visual field of the camera. Therefore, whether or not a detected shuttlecock trajectory is part of the previous shuttlecock trajectory must be determined. If the distance from the end of the previous shuttlecock trajectory to the start of the current shuttlecock trajectory is within a given range, then the current shuttlecock trajectory is determined to be part of the previous trajectory; otherwise, the current shuttlecock trajectory is classified as being unrelated to the previous trajectory.

1.5 Judging the stroke type of a moving shuttlecock

After detection of the shuttlecock trajectory, the stroke type is determined by comparing the data of the detected shuttlecock trajectory and the stroke definition. In the present study, the defined stroke types include lob, raise, smash, backstop, punch, and whip.

A number of parameters are used to determine the shuttlecock type. These are the trajectory length, the position of the trajectory start point, the position of the trajectory end point, the direction and the distance of the line from the trajectory start point to the end point, the trajectory camber, the average distance between points on the trajectory, the location of the highest point on the trajectory, the distance between the trajectory start point and the end point to the players, the distances from the start point and the end point to the badminton net, the direction number of the trajectory, the coordinates of the badminton net, the coordinates of the court contour, and the locations of the trajectory start and end points in the badminton court.

Flow chart of the detection system is shown in Fig. 2.

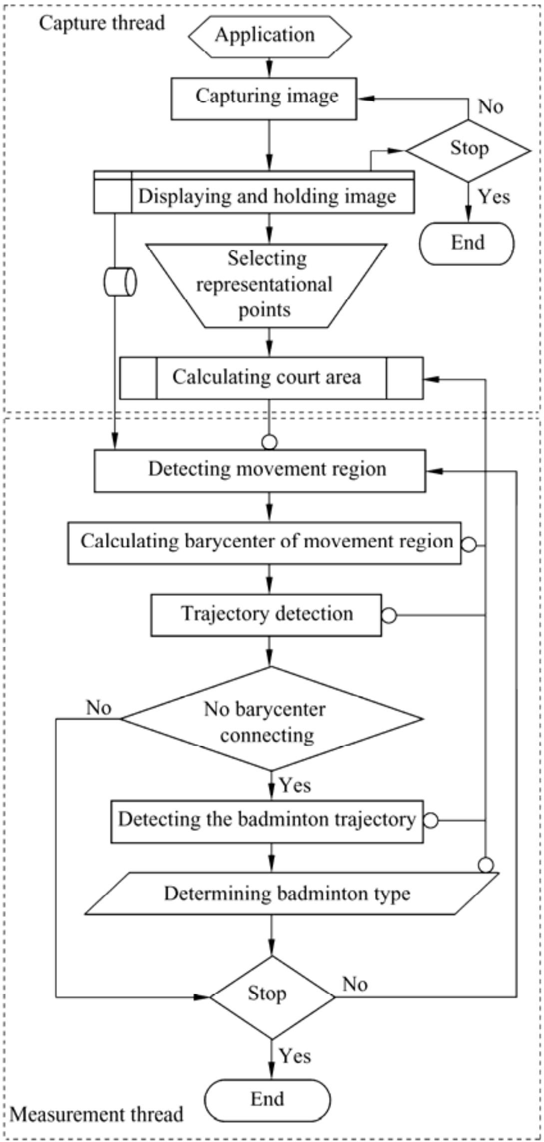


Fig. 2 Flow chart of the detection system

2 Results and Discussion

2.1 Sampling the moving shuttlecock

The real-time statistical data collection system requires the captured image to cover the entire badminton court, and sufficient space between the top of the net to the top of the image is required in order to achieve required measurement precision. As shown in Fig. 3 for the captured images, the top of the net was located just above the center of the image and the field of vision covered approximately the entire badminton court, indicating that the requirements for camera position and angle were satisfied.

Fig. 3 Badminton field

Tests revealed that a capture frequency of 40 frames/s was adequate for capturing even the fastest shuttlecock during a badminton match. Therefore, in the present study, the capture frequency was set to 40 frames/s. The algorithm was analyzed using four video samples and was tested at a training center. The frame counts for the four video samples were 394, 1204, 3108 and 6020. The average saving speed for the video samples was 38 frames/s; this can be improved by using a higher-capacity computer.

2.2 Measuring the moving shuttlecock

In obtaining the position information of the badminton court and net, a small number of characteristic points have to be demarcated before measuring the shuttlecock trajectory. This position information is important for determining the stroke type and for delimiting the badminton court in order to avoid noise from outside the badminton court. Figure 3 shows eight characteristic points that were obtained by manually clicking on the image. The lines indicate the area of the badminton court calculated using these characteristic points.

Statistical data for the athletes on both sides of the net must be recorded while analyzing the shuttlecock trajectory. The direction of the shuttlecock trajectory can be determined according to the direction number at the end of the trajectory. If the direction number is positive, indicating that the shuttlecock moved from left to right, then the measurement data should be added to the record of the athlete on the left side of the net. Otherwise, the measurement data should be added to the record of the athlete on the right side of the net. Tests revealed that use of a direction number to determine the trajectory direction provided correct results. The direction number was not only used to determine the trajectory direction, but also the length of the trajectory.

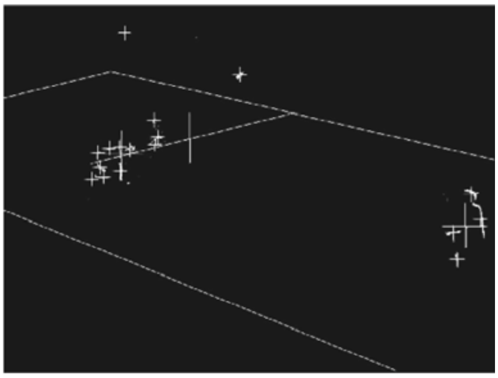
Figure 4 shows a difference binary image together with the two original images used to create it. Original image 2 appeared after the Original image 1 in the image sequence. The threshold for the binary realization was set at 5 for the difference image. Moving parts in the images, such as the shuttlecock and players, are denoted as white pixels; the static parts, such as the badminton court and the badminton net, are denoted as a black background in the binary image. Such binary images were obtained continuously from the image sequence, and each barycenter of each moving object was determined.

The large "+" symbols on the net line in the binary image (Fig. 4c) indicate the center of the net line. The two large "+" symbols on the players indicate their barycenters. The smaller "+" symbols on each of the white pixels indicate the barycenters of these pixels. The barycenter of each player was calculated correctly by using the block barycenter of each white pixel in the fixed measurement area. The borderlines of the measurement area, which are denoted by the white lines on the binary image (Fig. 4c), are drawn on the image view.

Figure 5 shows the barycenters for a single image and also the superimposed barycenters for a series of images. It is difficult to separate the barycenter of the shuttlecock in one single image from those of other moving features (Fig. 5a), but the trajectory of the shuttlecock barycenter can be clearly identified from inspection of the superimposed image series (Fig. 5b). The trajectory of other moving features, such as the players and

(a) Original image 1

(b) Original image 2



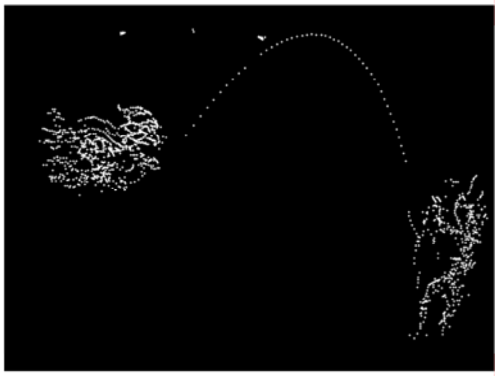
(c) Binary image

Fig. 4 Original images and binary image

their rackets, differ from the shuttlecock trajectory (Fig. 5b). Diagnostic data were recorded by connecting each barycenter with a trajectory, and the shuttlecock trajectory was determined by the analysis of these diagnostic data.

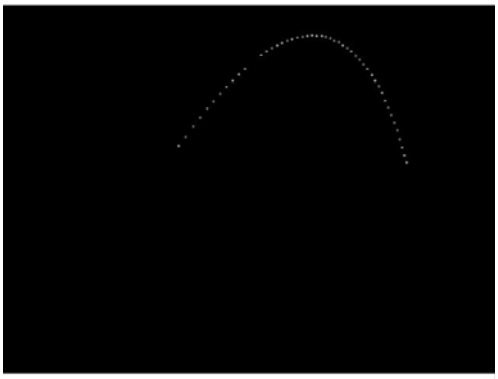
Figure 6 shows two samples of the moving shuttlecock trajectory detection. Figure 6a shows an intact shuttlecock trajectory, and Fig. 6b shows an interrupted shuttlecock trajectory. The trajectory data are subsequently used to judge the trajectory type of the moving shuttlecock.

(a) Barycenters of one image



(b) Barycenters of seriate images

Fig. 5 Barycenters of objects



(a) One ball track

(b) Interrupted ball track

Fig. 6 Samples of detected ball track

The detected trajectory data were compared with a set of stroke type definitions to determine the stroke type. The results obtained by the algorithm were compared with those obtained from visual inspection of the video samples, which included a total of approximately 10 000 scenes. The results are compared in Table 1. Video samples 1, 2, 3, and 4 had 394, 1204, 3108, and 6020 scenes, respectively.

Table 1 Measurement results by the algorithm (A) and visual inspection (V)

Video sample	Lob		Raise		Smash		Backstop		Punch		Whip	
	A	V	A	V	A	V	A	V	A	V	A	V
1	–	–	2	2	2	2	–	–	1	1	1	1
2	2	2	9	9	3	3	1	1	6	6	1	1
3	9	9	9	9	2	2	3	3	8	8	20	20
4	6	6	28	29	16	16	6	6	13	13	4	4

As shown in Table 1, the detection rate of the shuttlecock track was close to 100%. In only one case, a raise stroke, the shuttlecock track was not recorded. In this case, the shuttlecock trajectory was in fact determined but ignored because the shuttlecock trajectory was not the longest trajectory among the group of trajectories.

The test results indicate that the algorithm can be used to obtain statistical data of player tactics during a badminton match.

3 Conclusions

This paper described a method to obtain statistical data of a badminton match based on 2-D seriate images. Moving portions of the images, including the shuttlecock, rackets and players, are detected and labeled as white pixel blocks based on an image difference method. The outline of each white pixel block is measured in the binary image, and the barycenter is calculated from this outline data. Each barycenter point is connected to a moving track according to several data. The shuttlecock trajectory is extracted from the trajectory data. After the shuttlecock trajectory is determined, the stroke type is determined by comparing the trajectory data to the definition data for various stroke types. This process is continued until the end of each badminton match. The output is a set of statistical data of the stroke type for each player.

The algorithm can be used not only for the training and sports match, but also for other automated analysis, such as the track of the insects. In the future, we hope to accomplish three objectives: (1) improvement of the algorithm to identify the objective track even when the track is greatly disturbed; (2) improvement of the algorithm to allow a more detailed definition of the stroke type; and (3) improvement of the algorithm to enable the score of the badminton match to be judged.

Acknowledgements

This study supported by Beijing Modern Fubo Technology Ltd. We thank Dr. Sun Ming, at China Agriculture University, Ms. Wang Kaizhen and Mr. Zhou Zhihui, at Beijing Sports University, and Mr. Chen Yao, at the Pingpong and Badminton Center of China National Sports Ministry, for their help in this study.

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