An Automatic Visual Analysis System for Tennis

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October 18, 2012

Abstract

This article presents a novel video analysis system for coaching tennis players of all levels, which uses computer vision algorithms to automatically edit and index tennis videos into meaningful annotations. Existing tennis coaching software lacks the ability to automatically index a tennis match into key events and therefore a coach who uses existing software is burdened with time consuming manual video editing. This work aims to explore the effectiveness of a system to automatically detect tennis events. A secondary aim of this work is to explore the benefits coaches experience in using an event retrieval system to retrieve the automatically indexed events. It was found that automatic event detection can significantly improve the experience of using video feedback as part of an instructional coaching session. In addition to the automatic detection of key tennis events, player and ball movements are automatically tracked throughout an entire match and this wealth of data allows users to find patterns in play which have never previously been analysed. Player and ball movement information are integrated with the automatically detected tennis events and coaches can query the data to retrieve relevant key points during a match or analyse player patterns which need attention. This coaching software system allows coaches to build advanced queries, which cannot be facilitated with existing video coaching solutions, without tedious manual indexing. This article proves that the event detection algorithms in this work can detect the main events in tennis with an average precision and recall of .84 and .86 respectively and can typically eliminate manual indexing of key tennis events. The user interface provides a novel user query panel which coaches can use as a graphical query tool to retrieve and playback video of strokes played by a player from a specific region of interest on the court. A user evaluation of this interface is also presented. Evaluation of the system has also found that patterns in a player's tactics can be inferred, which may help to gain a competitive edge.

1 Introduction

Tennis is one of the most popular court based racquet sports in the world because of the relative simplicity of the rules and the small amount of equipment needed. A major aim of tennis coaching is to provide feedback to athletes to improve performance. While there are many aspects of performance that can be enhanced (e.g. physiology, biomechanics, psychology), recent sub-discipline of sport science have emerged (Performance Analysis and notational analysis) which aim to objectively record performance so that key elements of that performance can be quantified in a valid and consistent manner [1] [2]. An extremely common method is to video record a (tennis) match and identify all of the key events (strokes), e.g. [3]; [4]; [5]. Subsequently, the coach would review this information to perhaps: (i) quantify the patterns of play, and/or (ii) identify if positive/negative outcomes are associated with a particular technique or tactic. The video recordings themselves do not necessarily directly quantify aspects of performance (e.g. measure technique or tactic) they simply provide the coach with an accurate and objective record of events, in comparison to self-recall which is inaccurate and biased [2] [6]. The coach reviews the recordings to use their experience and expert knowledge to infer technical, tactical or mental strengths and weaknesses related to performance.

While there are a variety of uses of such video-based playback systems, a central requirement for them is the identification and indexing of key events. To date this has invariably been completed through a manual process, where each action/event in the recording is tagged by the user. This however is a very time consuming process. A solution to this would be the production on an automated system that could record tennis matches and automatically index the match into key tennis events. Coaches could then review and quantify instances of indexed events as a visual coaching aid. To the best of our knowledge only one system (Hawke-Eye Coaching) has been developed which automatically indexes events. However a major limitation of this system is that it cannot index specific strokes played. Automatic indexing has not been achieved in any other sport to the best of our knowledge. The main technological advancement has been in verification of referee decisions, which has been very popular in professional tournaments. In assessing how best to present information to guide the coaching process in tennis, [7] argue that a combination of both visual and verbal strategies can be effective if used correctly. In fact, empirical evidence has suggested that in tennis, the use of videotaped replay and loop-film technique has merit and can be given consideration for use in instructional settings [8].

After analysing coaching practices with existing coaching tools and conducing a series of interviews with various coaches to extract user requirements, this article presents a group of tennis events which can be automatically indexed, with only one assumption, that a tennis match follow the rules of tennis as laid down by the International Tennis Federation[1]. With less event indexing required, a coaching session environment is a more simplistic task than a competitive match environment, so this research article focuses on competitive matches. An earlier version of this system with fewer features was previously published in [9] and this article brings the different components together and provides an interface for coaches for tactical analysis.

The level of detail provided by the proposed system has never been automatically indexed before and a major challenge, which this paper overcomes, is to infer events from multiple cameras and efficiently store this data in an organised manner to facilitate verbal and visual coaching methods. This work does not automatically detect scores or set boundaries, but this is targeted for future research. A user study has been conducted in the present paper where coaches were asked to perform tasks which simulate real life visual and verbal coaching routines. The findings from the user study in the present paper is that coaches believe that using this system as a visual coaching aid can improve their coaching effectiveness. This is because this system can automatically index key tennis events and the retrieval system presented in this article can easily highlight events for a coach, which would otherwise require an enormous amount of manual indexing. It should also be noted that because no manual editing is necessary, using this system will not negatively impact on a coaches' day to day duties.

In addition to the automatic detection of key tennis events, player and ball movements are automatically tracked throughout an entire match and this wealth of data allows users to find patterns in play which have never previously been analysed. Player and ball movement information are integrated with the automatically detected tennis events and coaches can query the data to retrieve relevant key points during a match or analyse player patterns which need attention. This level of querying reduces the time a coach will spend manually indexing video. Two additional contributions within the user interface are the Virtual Rally Simulator and the User Query Panel. The Virtual Rally Simulator replays the ball movements on a graphical court and since only the ball movement is visible, the viewer will focus on the ball only and not be distracted by other visual presences which are present in actual video. The User Query Panel is a visual search tool whereby users can visually construct queries on a graphical tennis court to retrieve specific strokes played from a given region, whilst an opponent is located in another specified region. Although customised for

[1] http://www.itftennis.com/technical/rules/

tennis, it is possible that this system could be adopted for similar court sports such as badminton in the future. The main research aim of this work is to explore the effectiveness of a system to automatically detect tennis events using visual sensors. A secondary aim is to evaluate the benefit of an event retrieval system which coaches can use to efficiently retrieve and playback automatically indexed events.

2 Existing Sports Coaching Software

The role that information and communication technology has played in sports coaching has dramatically increased in a wide range of areas in recent times, including performance feedback [10]. Indeed, video technology has long been used as the popular feedback modality to record training sessions, in order to train a sports athlete. Yamagiwa et al. [11] have stated that video analysis can provide a platform for a coach to provide feedback to an athlete in way that can be easily understood by an athlete. Because of this, many professional coaches have recorded training sessions or competitive matches involving their own athletes and used standard video playback functionality to help illustrate to the athlete, where he/she can improve performance. In [12], the authors performed experiments to establish if short tennis skills transferred to lawn tennis. In these experiments fourteen tennis players were coached for several hours and the coaching sessions were video recorded. The video was later analysed by three coaches in terms of backswing, positioning (position where player stood in reference to the bounce of the ball), follow-through, and placement (accuracy with which the ball was hit). This is an example of how the coaching session is aided with video, however it is the belief of the authors of this article that if the events being examined in this example (i.e. stroke execution), were to be automatically indexed this would reduce the amount of time a coach spends video editing and this would in turn improve the coaching experience.

2.1 Video Analysis Tools

The ability of analysis software to archive information can give sports teams the competitive edge over their opponents. Analysis systems can also be used to illustrate tactical operations. Although there are many processes which can influence the coaching cycle, such as a coaches' experience and biomechanical systems for example, this work only focuses on coaching through video analysis. Hailes et al. [13] state that advances in video software technologies are making instant video feedback more commonplace. Visual analysis tools such as Vidback[2] are examples of commercial offerings today which are widely used in sport, while Dartfish Simulcam and Dartfish StroMotion[3] provide the coach with visual editing techniques only possible with high end production systems in the past. It should be noted that all these video coaching tools are portable

[2]http://www.simi.com/en/products/vidback/index.html
[3]http://www.dartfish.com

by nature and each vendor assumes that the coach has access to a camcorder to capture video streams and a laptop to ingest the media files into the respective video coaching applications.

2.2 Instrumented Sports Coaching Environments

An instrumented coaching environment is a coaching system which requires a permanent hardware installation at the sporting venue in order to capture information. Hawk-Eye Coaching[4] is an example of an instrumented coaching environment, with customised installations for tennis or cricket. Hawk-Eye Tennis Coaching System provides a number of interesting features which include, ball spin during a serve or ground stroke, where the ball bounced and where returns are played from. Hawke-Eye coaching is independent of the popular Hawke-Eye umpire system which is used in professional tennis tournaments to assist umpires in gauging whether a ball bounced inside or outside a line.

ProZone[5] provides a soccer analysis framework by instrumenting a football pitch with high quality cameras. ProZone provides semi-automatic frameworks for indexing sports video. The ProZone system (which, due to the cost of installation and game analysis costs, is generally only used by professional teams) uses eight cameras placed around a stadium to track players during a match. Each player (and official) is tracked via a semi-automatic process. The system employs a computer vision algorithm in which players are segmented by background subtraction from a static background image, thresholding and connected component analysis. Each player is then temporally tracked automatically. However, where there is a conflict, such as several possible players within close proximity or no possible choice of player, then the tracks are manually annotated. In addition to tracking players, events such as free kicks, corners and passes are all manually annotated. When a player touches the ball, this is recorded by clicking the correct event from a displayed list to indicate the event type. This ball data, combined with the position coordinates derived from the player locations, creates a ball trajectory data set. Both the player, official and ball data can then be employed to calculate tactical and statistical data. This style of instrumented visual analysis system is widely employed in soccer stadiums and is very expensive and its semi-automated operations results in a high amount of user input.

2.3 Limitations of Existing Solutions

Approaches for visual event indexing for tennis have been previously reported [14] [15], however there has been no coaching system which is facilitated by automatic stroke recognition in tennis or any other court sports such as badminton or squash. Issues with existing instrumented sports coaching tools such as Hawke-Eye Coaching include its inability to automatically recognise which

[4]http://www.hawkeyeinnovations.co.uk
[5]http://www.prozonesports.com/

(a) Overhead (b) Baseline 1 (c) Baseline 2

Figure 1: Three camera preset configurations required to automatically index a match into key events

player has executed a stroke during play (due to change of ends) and most importantly its inability to recognise the stroke type played, which is essential for enabling coaches to generate high-level tactical queries. None of the existing solutions can automatically track a player over an entire match and this means that a coach will need to spend time manually annotating video after or during a capture session. Another drawback of existing instrumented coaching systems is the high cost associated with all these systems.

With commercial video coaching tools, coaches need to spend endless hours manually editing video after a capture, which is extremely time consuming and is a detrimental burden on coaching teams. This article presents the first fully automatic event indexing system which is driven by automatic stroke recognition, along with player and ball localisation. A semi-automatic event indexing system may allow coaches in the future to index another level of detail and this is discussed in Section 8, however this article focuses on the potential of automatic indexing.

3 Infrastructure

This section outlines the minimal sensor technologies required by this system to obtain a visual event recognition system for competitive tennis. The visual instrumentation consists of three low cost cameras, with pan, tilt and zoom (PTZ) capability. One camera provides an overhead view of the court and the other two baseline cameras are positioned at either end of the court. The two cameras at the center of the baseline at either end of the court are AXIS 215 PTZ cameras, which are positioned 2.8 meters above the court and have very high zoom functionality, as well as physical pan and tilt. The overhead camera is positioned at 13.8 meters from the ground. This camera is an AXIS 212 PTZ camera, which has a wide angle lens (140°) and includes fast digital PTZ functionality by sub sampling from a high-resolution sensor. All the cameras have a resolution of 640x480 and a frame rate of 30Hz. The user interface in this article can playback additional cameras for visual feedback, but automatic tennis event detection only requires the three cameras mentioned above.

The infrastructure used in this article may be assembled indoor or outdoor. In the case of an outdoor setup, two 13 meter poles at either side of the net could be assembled and a cable could run from the top of one pole to the other. A single aerial view camera would then be mounted to the centre of the cable to capture the overhead movements of the ball and players. This instrumentation could be installed at low cost. Expensive aerial view instrumentations are common nowadays to capture overhead shots of American football games in action and also in soccer pitches. In both American football and soccer, the camera is mobilised via a network of overhead cables, to allow it to move across the field, making each instrumentation much more complex than would be required in tennis. As long as the court surface is not yellow in colour, which is the colour of a tennis ball, ball tracks can be easily inferred from an overhead camera using the approach described in the following section. In relation to the specific camera calibration, we used the following Pan Tilt Zoom (PTZ) coordinates; Overhead Pan = $-5.2°$, Tilt = $-7.4°$, Zoom = 2955; Baseline 1: Pan = $-94.4°$, Tilt = $-25.8°$, Zoom = 1; Baseline 2: Pan $-87.8°$, Tilt = $-30.0°$, Zoom = 1. Where the zoom range is 1-10000.

4 Automated Tennis Event Indexing

This section details the engineering process to automatically index specific tennis events using three cameras as described in the previous section. We first detail our requirements gathering process which was conducted using interviews with coaches. Then we describe the event detection process used in this work, before evaluating the efficiency of the event detectors.

4.1 Interviewing Process

To understand which events within a match are of interest to coaches, a meeting was held with each tennis coach to determine an achievable set of requirements. The interview consisted of asking the coach which tennis events they would like to have automatically indexed and also if they use existing sports coaching software. If they did use existing coaching software, we identified which events the coaches manually indexed.

Four coaches were interviewed, two local club coaches and two national coaches who train elite players. Both local coaches have over 4 years experience coaching players who compete at club level competition, both have a Level 1 coaching certificate and they coach at least 12 hours a month. One of the national level coaches who were interviewed has been a qualified coach for fifteen years and is qualified to Level 3 under the Tennis Ireland coaching certificate and coaches for at least 35 hours per week. This coach was a top national player during his playing days (Rank No. 1 in Ireland). The second full time coach has been qualified for five years and holds the Tennis Ireland Level 2 certificate and coaches on average of 35 hours per week. Both full time coaches have experience coaching players on the Association of Tennis Professionals (ATP), International Tennis Federation (ITF) and Woman Tennis Association (WTA) tours.

From these requirements gathering interviews a set of events which could be automatically indexed was formulated. The following events were decided upon by analysing what events coaches currently index: Serve type (T, Body, Wide), first serves made/missed, return of first serves, return of second serves and strokes which hit the net. Through interviewing the tennis coaches it was also learned that player and ball positioning would also be a useful statistic if there was an interface where coaches could run queries based on the locations of players and ball movements. Coaches all expressed a desire to be able to run queries to retrieve the number of occurrences where a player plays a specific stroke from inside a user specified area on the court. Coaches also agreed that a tool to find the start and end of rallies within a match and be able to index them according to the final stroke played in the rally or the duration of the rally would be a useful component for finding patterns of interest. Coaches remarked that this level of detail is simply too time consuming with manual indexing, but can help to determine interesting patterns in a play. It was found that coaches who use existing coaching software tools manually index forced/unforced errors, but this was not possible using the proposed automatic event indexing tools.

4.2 Event indexing

This article does not address automatic detection of scores or unforced/forced errors, both of which were sometimes manually indexed by the coaches. In relation to forced/unforced errors there is certainly scope for a semi-automatic event indexing approach to accurately detect forced/unforced errors and this is also a target for future research. It was also found that coaches record the frequency with which an event occurs and this event frequency counter has been built into this user interface. Using the two baseline cameras and a single overhead camera (as shown in Figure 1), a complete event recognition system for tennis using video only was developed. The following sections describes the process used to automatically index events using video.

4.3 Player and Ball Tracking

Using the overhead camera, algorithms have previously been developed to detect the player and ball tracks [16]. The tennis ball is tracked using motion images for ball candidate detection followed by linking candidates into locally linear tracks. The ball track gives the time and location of the origin of a ball hit and then the X, Y movement of the ball, along with the time until it stops. The stroke type is unknown at this point. To detect both players from the aerial view camera, background subtraction and hysteresis-type blob tracking are used to track the tennis players positions.

4.4 Serve Detection

Using the data from the player tracks as described in Section 4.3, it is possible to locate both player's positions and map these coordinates to the tennis court to determine each player's location on the court. Then, by determining both players' locations on the court at all times during a match, the algorithm can recognise a serve event. The serve event is detected when a player is located inside a serve zone for two seconds whilst their opponent is inside the diagonal return zone for five seconds and a ball hit occurs from the server's side of the court. The details of this approach was previously published in [9].

4.5 Change of End Detection

Robust player identification and game identification is based on change of end times. Three steps are used to detect a Change of End, the first two are novel and the third step has been previously published in [9]. *Step One* uses serve direction patterns (see Figure 2). Essentially this step uses the constraint from the ITF rules that there is only one change of end (COE) event for every change of serve direction event (COSD). Serve direction can be defined as the direction the ball travels after it is struck by the racquet, during a serve.

In *step two*, the best candidate for a change of end event between two COSD events is detected. Player tracks are used to retrieve a temporal location where both players approach and/or walk from one side of the net to the other, as they will need to walk past the net at the change of ends. If this step finds more than one candidate change of end event (CCOE), between two COSD events, step three is required to check if there is a new player serving after a candidate change of end event.

Step Three exploits a recent fashion trend in tennis where players tend to wear colorful clothes. This trend can be credited to the fact that most professionals nowadays are sponsored by clothing companies and as a result of this amateur players tend to wear distinguishable clothing too. For every CCOE, the rear view camera is used to inspect the colour features of a serving player in the previous serve and next serve. To identify if a new player is serving, the previous serve is flagged and 60 frames are extracted from the rear view camera. The player is extracted as a colour foreground from each image and the resulting HSV image is then split into three channels (Hue, Saturation and Value). The first two channels are discarded (Hue and Saturation), as analysis concluded that the Value channel alone provides sufficient information to accurately detect a change in the player's appearance. An image histogram is then generated from the Value channel, which represents the brightness in the player foreground. The same image processing technique is then applied to the next serve after the candidate change of end and the similarity distance between the histogram for the previous serve and the next serve is calculated using the Bhattacharyya coefficient, which has been widely used to compare image histograms [17]. A new player is deemed to be present in the image when the difference between the previous and next serve exceeds a threshold.

4.6 Backhand and Forehand Detection

One obvious difference between a backhand and a forehand is the positioning of the ball in relation to the player (left or right of the player) during the execution of a stroke. This heuristic is used to detect forehands and backhands from the overhead camera. Firstly, the system automatically removes the serves from the collection of ball hits. For each remaining ball hit in turn, ball tracks for that stroke are used to find the origin of the stroke and the (x,y) position of the ball at the start of the stroke. The player as foreground is then extracted from the video and from this the centroid of the player as shown in Figure 4 is obtained. This provides the position of the player and the position of the ball at the beginning of a stroke. The algorithm then detects whether the ball is above or below a player at the start of the stroke and since it can be detected whether a player is right or left handed with the dominant arm detector (described in the following section), this algorithm can finally infer if a stroke is a forehand or backhand.

4.7 Dominant Arm Detector

The biomechanical movements of a typical serve are quite similar from one player to another. However, there are clear differences between left handed players and right handed players in that left handed players will throw the ball upward with their right hand and swing the racquet with their left hand, while the reverse is true for right handed players. Using this biomechanical observation, this system can automatically infer if a player is left handed or right handed using the camera behind the baseline as illustrated in Figure 3. First, the player is segmented as the foreground object for each image in a serve. Although the contour features that are used are robust to foreground holes and noise in the extracted silhouette, they can be adversely affected by shadows. For this reason, a layered background model is used that includes robust shadow detection [18]. To extract contour features, the player foreground region is divided into 16 *contour segments*, centered on the player centroid. Over the entire stroke, contour features are calculated for each video frame. The features are then normalised in order to make them invariant to the player's distance from the camera. A binary Bayesian classifier [19] was trained on samples of left handed players serving and right handed players serving. At the beginning of each match, the first five serves from each player are used as input vectors and the classifier identifies in which hand the player is holding the racquet.

4.8 Rally and Game Detection

The occurrence of a rally can be inferred by detecting all the non-serve strokes which occur between two serves. The start of a new game can be inferred from serve detection by recognising when the serve switches from Player A to Player B and vice versa. Tie-break games are easily detected using a rule-based algorithm since the serve direction will change after the first point in a tie break

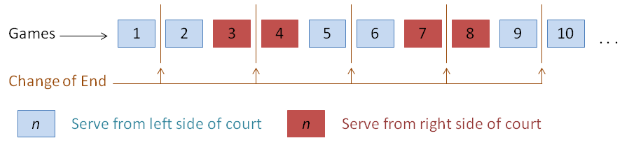


Figure 2: Pattern for serve direction and change of end, one change of end occurs for every change of serve direction

game and every two points thereafter.

(a) Camera image (b) Foreground (c) Radial map

Figure 3: Contour feature extraction.

4.9 High-level Query Generation

Each of the following high level events is indexed by merging data from the key tennis events. Having detected the strokes played, along with the player and ball tracks, the movement of the ball is detected after a specific stroke is performed by a given player. An offline rule-based query then detects if the serve is a **T, Body or Wide**. A T serve is when the ball intersects with the middle of the T zone in the opponents service box after it has bounced in the service box. A body serve is when the ball crosses the opponents service box at roughly the middle of the box. A wide serve is when the ball exits the

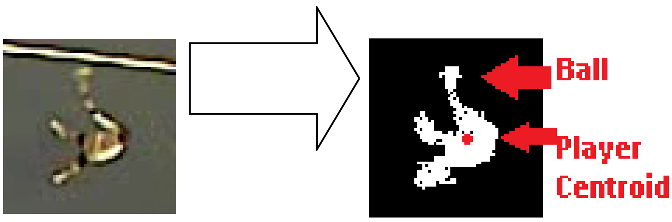


Figure 4: Player centroid and ball location are compared on the y-axis to determine if the ball is struck above or below a player

opponents service box at the close to the court boundaries. A similar rule-based query detects if a forehand is **in-to-in, in-to-out, cross, line** or a backhand is a **cross, line**. A **forehand in-to-in** originates from the players left side of court and the ball continues down the left side into the opponents half of court. A **forehand in-to-out** originates from the players left side of court and the ball then travels diagonally across the court into the opponents side of the court. **Forehand line** originates from the players right side of court and the ball continues down the right side into the opponents half of court. **Forehand cross** is when the ball is struck from the players right side of court and the ball then travels diagonally across the court into the opponents side of the court. A similar coordinate system is used to find backhand cross and backhand line strokes.

A rule based query engine is executed offline to identify **first serves made/missed**. This module uses heuristics based on the server's movements immediately after a serve. The rules of tennis state that if the first serve is illegal, the second serve must be taken from the same side of the baseline. Therefore if a serve is executed and the servers location remains on the same side of the baseline for the next serve, it can be inferred that the previous serve was missed, otherwise the first serve was made. Following on from the knowledge of first serves made/missed, the strokes played by the returning player are analysed offline to infer the **return of first serves** and **return of second serves**. A rule-based query identifies which player is returning and what type of stroke is being executed.

Ball tracks are used to detect which strokes result in the ball hitting the **net**. This query simply records the origin of a each stroke played. If the ball track terminates in what is defined as the net region, it is assumed that the ball has hit the net. A **volley** is usually played when a player returns the ball, while positioned close to the net, hence the ball does not have time to hit the ground and is volleyed. To detect forehand and backhand volleys, a query detects forehands and backhands and then cross examines each detected stroke with the relevant player track to infer if the player is within volley range of the net.

5 Experiments

This section details the experiments for measuring the accuracy of detecting the key tennis events. Accuracy results are provided for the key tennis events.

5.1 Dataset

Twelve complete matches were recorded with players of various skill levels, corresponding to 825 minutes in total. A ground truth was generated offline by manually annotating each tennis event. It took 90 minutes on average to manually annotate a single match of 180 minutes in length. Each match was the best of three sets, played according to the rules of ITF. The video data was recorded from all three cameras. To categorise players by skill level, we classified a player into either beginner, intermediate or advanced skill level. This was implemented in terms of years played and times per week. An advanced player was deemed to be a player who has played for more than six years and plays at least once per week. An intermediate player was any player who has been playing from two to six years and plays twice per month. Beginner players are those who have been playing for less than two years, but only play once per month.

Advanced players were recruited by contacting two local tennis clubs. Four players were recruited who compete in both local and regional competitions. The remaining eight players who were recorded are members of a tennis club society in a university. Six of these players are considered beginners, while the remaining two players had only started playing tennis. The diversity in skill levels is necessary to examine if events played by players from various skill levels can be automatically indexed.

5.2 Event Detection Procedure

A ground truth of each match was used to measure event detection accuracy for each event. When all the matches were fully indexed, the median score of how accurately each tennis event was indexed over all the matches in the dataset was calculated using Precision and Recall [20].

Event	**Method**	**Precision**	**Recall**
Serves	Serve Zones	.79 (6.1)	.82 (9.1)
	Ball Hits	.68 (11.5)	.88 (9.3)
Forehand & Backhand	Left/Right	.71 (11.1)	.84 (9.1)
	Overhead Pie Features	.74 (8.9)	.77 (8.2)
Dominant Arm	Baseline Pie Features	1 (0.0)	1 (0.0)
Change of End	Histogram Differential	1 (0.0)	1 (0.0)
Rallies	Inferred	.78 (8.2)	.71 (8.4)
Games	Inferred	.75 (19.4)	.75 (19.6)

Table 1: Tennis event detection results using visual sensors. Median (Standard Deviation) for overall event detection for different matches is included within brackets

5.3 Event Detection Comparison

A comparison of how well each sensor is able to detect each event is given in Table 1. This table gives the median score of how accurately each sensor can detect a given event when tested on all the matches in the dataset. If a serve, forehand or backhand event was indexed to ± 1 seconds it was considered a correct match. A change of end event needed to be indexed anywhere between the end of one game and the first serve of the following game to be correct. Rallies were considered correct if indexed to ± 2 seconds, while a game was considered correct if indexed to ± 10 seconds. In relation to Table 1, precision is the number of correct results returned, divided by the number of all returned results. Recall is the number of correctly classified results divided by the number of results that should have been returned. Both precision and recall are commonly used metrics for measuring the performance of event detection in engineering [20].

The change of end detector is significantly improved by the first two filtering steps. In fact, player tracking (Step 2) was usually all that was required to detect the change of end event, but sometimes the players would collect balls at the net and therefore Step 3 was invoked to find the best candidate change of end between two change of serve detection events. In the event of no change of end event being detected between two change of serve direction events, the system will flag an anomaly at the next change of serve direction event (see Figure 2) and correct itself, by using the change of end times. When all the core tennis events are indexed, it is straightforward to infer other events, such as first serves made/missed, return of first/second serves, and when a player hits the net, for example. Precision and recall results for these further events are not provided as they are simply an amalgamation of the core events in Table 1 and the player and ball tracks.

6 Match Point: Visual Coaching System

In this section a coaching system is introduced which coaches and players can use to playback tennis events and analyse play statistics. The system is called Match Point and the user interface (Figure 5) consists of three main panels. The *Match Timeline* displays all the matches played by a given player. Each time line represents a single match. The *User Query Panel* allows users to draw a rectangle for each player and also a stroke direction. The user can then retrieve all strokes which are played while both players are simultaneously inside their respective rectangles. This graphical tennis court is also used as the Virtual Rally Simulator. The *Events Panel* provides an interface for users to build specific queries related to stroke patterns such as “play each video instance in the match where Player A performs a first serves missed event, for example. When a user searches from either the user query panel or the events panel all the results are displayed along the match time line and can be played in the video screen by clicking on that event.

6.1 Automatic Match Indexing

After the match has finished, the videos are ingested into the system simply by dropping them into the ingest folder. Additional match information is manually entered into the system such as the full names of both players. If either of the two players have been recorded by the system before, the user selects this player from the existing players menu. No further user input is required and the user can activate the automatic event detection algorithms by clicking a button. The algorithms are executed offline and can take several hours to complete depending on the duration of the match.

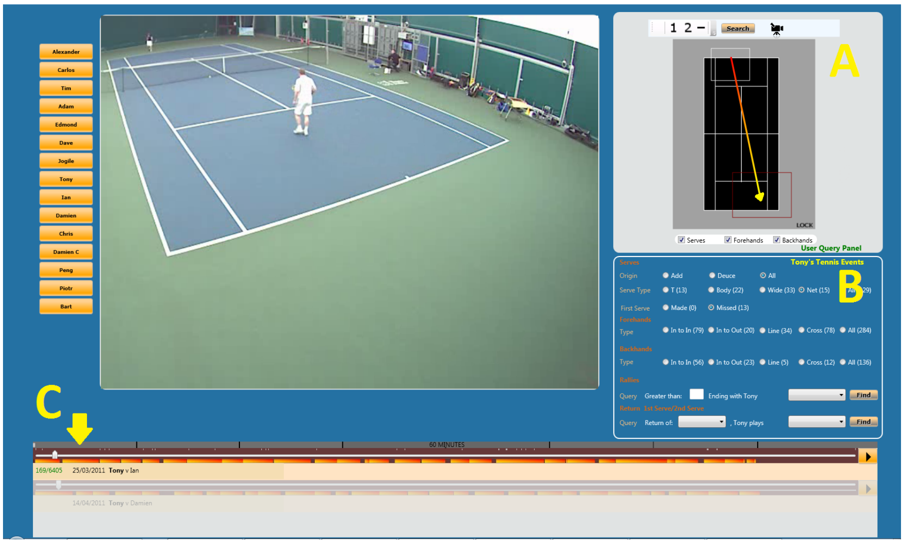


Figure 5: Match Point Event Retrieval System, (A) User Query Panel & Virtual Rally Simulator (B) Event panel to retrieve events (C) Match timeline panel is used to display events.

6.2 Match Timeline Control

To populate the match timeline with matches from a respective player, the user selects a player from the player panel on the left side of the interface. In the event that a player is captured in multiple matches, multiple match timelines will appear. Each match timeline also visualises all the games in a match. Each game is represented by a brown rectangle along the match timeline. The length of each game is clearly visible and coaches can focus on events which occur in short or long games with this feature. Additional information is also available here such as the player names, match date and match duration. When a user selects specific events from either the User Query Panel (Section 6.4) or the Events Panel (Section 6.3), all the retrieved events are displayed along the selected match time line control. Video playback is only possible by selecting an event from a match time line panel.

6.3 Events Panel

The events panel provides an interface for users to view match statistics and playback video of each event in the panel. For example, the user might want to view the video of all the T-Serves executed by *Player A* from the left side of the baseline. Each event retrieved will then be represented along the match timeline as a vertical tick and the user can click on the relevant event tick along the match timeline to playback the video of the event.

The events panel provides many analysis statistics and video playback of

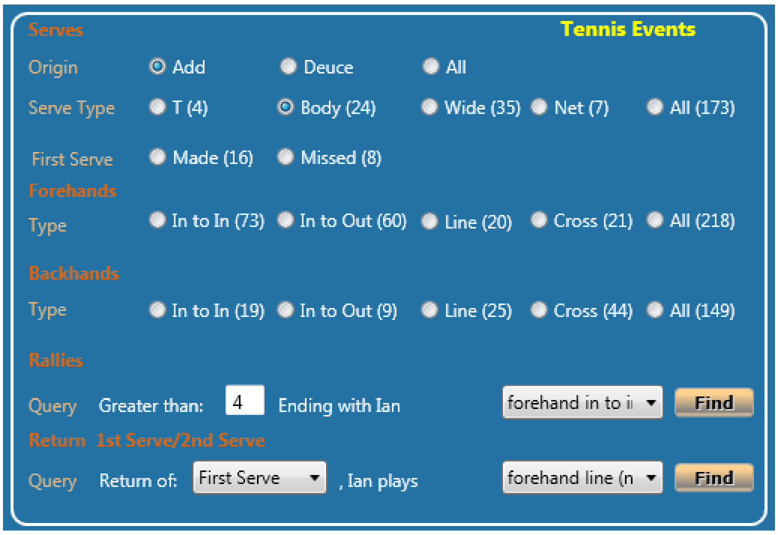
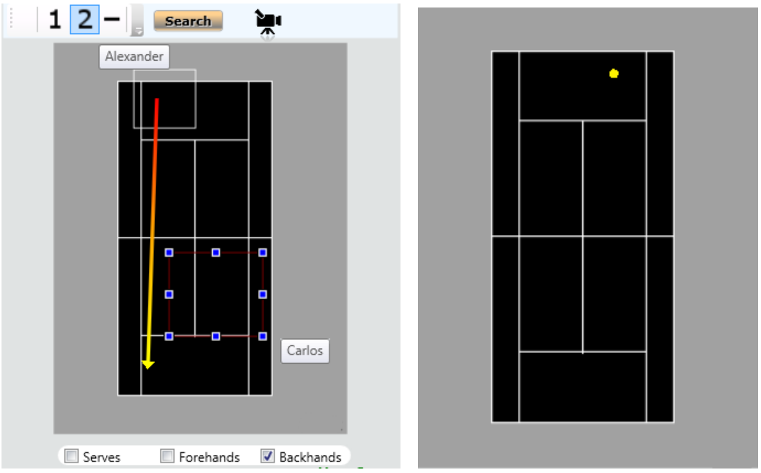


Figure 6: Illustration of the Events panel showing individual player statistics over a single match. The indices represent how often in the match the given player performs the specific event. Section 4.9 explains what the stroke sub categories are.

each event in this panel is instantaneous. The frequency of T, body and wide serves from the deuce and advantage side of the baseline is visible, which can be used to gauge if a player is under/over using a particular serve. This level of pattern finding in a player's play is easily highlighted with the event counter, which counts the frequency of each event as shown in Figure 6. In addition to serve subtypes, the event panel displays how many first serve events a player has made and missed and how may of these were T, body or wide serves, or those serves which hit the net.

The number of times a player performs a forehand in-to-in, in-to-out, cross, line or a backhand cross or line during a match can be analysed in the events panel. The events panel also contains the number of forehands and backhands which hit the net. Another useful playback feature is to find rallies which contain more than n shots where a given player ends the rally by hitting a particular stroke, where n is defined by the coach before searching. Finally the events panel can quickly playback a player's return of first or second serve during a given match. Video playback of all the aforementioned tennis events is possible by clicking on the relevant button in the events panel. This will populate the match timeline with each event and the coach can playback any event by scrolling through the match timeline.



(a) (b)

Figure 7: (a) User Query panel detects number of times a player performs a stroke from a given region of the court (b)Virtual Rally Simulator - Only the yellow ball is visible to illustrate ball movement during a rally without any visible distractions

6.4 User Query Panel

Coaches who were interviewed expressed a desire to be able to query strokes played from a specific region on the court. Since the system can record the player locations and stoke locations, a solution to the coaches requirements was to develop the User Query Panel, which aims to allow coaches to run queries based on strokes played from specific regions on the court. This is a specific contribution, which allows users to visually construct a query by drawing rectangles and line objects which represent both players' locations and the ball in flight. The user can then retrieve all strokes which are played from a given region of interest where the ball travels along a user specified shot line. It is also possible to filter the results returned by any combination of serves, backhands and forehands. Results are displayed along the match timeline for efficient and visual retrieval. Analysing the frequency with which players perform specific strokes from a given region on the court has been highlighted as a potentially useful feature by the tennis coaches who were interviewed.

The process to find all strokes played by a given player from a particular region on the court is as follows. A coach draws a rectangle anywhere on the court as shown in Figure 7(a), it's possible to draw one rectangle or two to find strokes played while both players are inside their respective rectangles. Finally the flight of the ball is inferred by drawing a ball line on the panel. Stroke types may be filtered using options as shown in Figure 7(a). The experiments in the next section illustrate how this feature performed in a user study.

6.5 Virtual Rally Simulator

As a tactical analysis feature, this section introduces a ball flight simulation tool which simulates the movement of a ball on a virtual court to put the focus on ball movement during a rally. Video is a great aid to coaches who are reviewing a previous match with a player. However real time video captures an abundance of visual information, such as the players and any court side presence. This visual ball simulation feature omits the players from the scene and this engages the players (watching in the presence of a coach) to really focus on the movement of a ball during a rally and not be distracted by watching the opponents movements or other visual presences found in 2-D video playback.

7 User Study

This section evaluates how practical this overall system is for tennis coaching. All experiments within the user study were videotaped to compile accuracy scores of the users ability to complete the test queries. After users had completed all experiments they were asked to anonymously complete a questionnaire. By making the questionnaire anonymous, users are given an unbiased platform to express their opinions on the overall system experience.

To evaluate the system, three experiments were conducted by ten users, six of whom were tennis coaches and four were regular tennis players. Four of the coaches were full time coaches and coach over 35 hours per week. One of these coaches was qualified to level 3, while two are qualified to level 2 and one holds a level 1 Tennis Ireland coaching certificate. The remaining two coaches all coach in local tennis clubs and coach five hours per week. All coaches agreed to independently evaluate the system presented in this article. The experiments evaluated all the components of the interface and a comparison of the user interface was made with Dartfish, which is a market leader in sports video analysis, but requires the user to manually identify events. Retrieval experiments were conducted in a room equipped with two desktop PCs, each with a 23 inch monitor, with an instructor present. Each user completed a training session to learn how to use this system in advance. A similar level of training was then provided for Dartfish, where necessary.

It should be noted that five of the six tennis coaches are Dartfish experts and two of the tennis players regularly use Dartfish. Four of the coaches were professional coaches and two coach in local tennis clubs. The four regular tennis players were sourced from a local tennis club. There are currently no automatic event retrieval systems for sports coaching, therefore the system presented in this article is compared to Dartfish, which is the most popular sports coaching analysis tool and has functionality for manual event annotation. Problems or questions on how to use each system were discussed during the training sessions.

7.1 Experiment One: Event Panel Evaluation

The aim of the first user experiment was to provide the users with a hands on experience of using the event panel in Figure 6 to retrieve various match events, which coaches regularly review for learning purposes. The users were given a task list of five events to retrieve using the events panel in the Match Point system. The events to be retrieved are shown below and were chosen by analysing which tennis events coaches have manually tagged using Dartfish in the past. A questionnaire was used to assess the user's experience and to assess whether coaches and players found using the event retrieval system beneficial for learning purposes. The outcome of this experiment is discussed in Section 7.5.

1. First serves made and first serves missed from the left or right side of the baseline. The user must also observe if the serve is a T serve, body serve, wide serve or net.

2. Return of first serve and return of second serve. The user must also observe if the return is a backhand cross, backhand line, forehand in to in, forehand in to out, forehand cross or forehand line.

3. Rallies, which are greater than four strokes and end with Player A playing a forehand in to in.

4. Rallies, which are greater than four strokes and end with Player B hitting the net whilst playing a backhand cross.

5. Rallies, which are greater than four strokes and end with Player A playing a forehand in to out.

7.2 Experiment Two: User Query Panel

This experiment aimed to investigate whether users can utilise the dynamic drawing features of the User Query Panel to accurately retrieve instances where a player performs a stroke played from a specified region of interest on the court. This experiment was carried out with ten users (six coaches and four players). To correctly retrieve an event, the user was shown an animation of a tennis court with two boxes which represented general locations of each player and a line to represent the ball trajectory. The user then had to construct the query on the User Query Panel. Each user was first trained on how to use the user query panel and then completed two training queries before being asked to retrieve the three queries below. When the results were displayed on the match timeline panel, each user was then asked to view each of the retrieved results for validation.

1. Find all serves played by Player A whilst Player B is located within a specified region.

2. Find all serve returns by Player B, which are backhands played from a given region of interest on the court.

3. Find all backhands which traveled a particular direction and were played by Player A from a given region of interest.

7.3 Experiment Three: Event Retrieval - Match Point vs Dartfish

The aim of the this experiment was to assess, in terms of system usability, which coaching interface is the most efficient user interface for event retrieval in the context of tennis video analysis. For this experiment, Dartfish was populated by manually annotating several matches with Dartfish and then tagging each match fully. Each user was then trained how to perform event retrieval on Dartfish and then asked to retrieve the five events from Experiment 1 using Dartfish. In this experiment, only the useability of the user interface is evaluated for both systems. No existing coaching software automatically annotates video into tennis events, therefore only system useability can be evaluated in terms of how well the interface performs, which is a very important factor in how well an athlete will assimilate information.

7.4 Evaluation Questionnaire

When each user completed all the relevant experiments, they were asked to fill in the following user questionnaire. These questions were designed to assess how well Match Point performs for coaches and tennis players alike. Questions 1 and 2 were duplicated from a well known source for user evaluation of computerised systems [21]. Questions 8, 9 and 10 were taken from Davis et al [22], which is a well used source for predicting user acceptance in computerised systems. The remaining questions were speicific to Match Point and directly question specific components of the Match Point system. All questions were answered by a score of how true the statement is (0 = false, 5 = true). Questions 8 to 10 were relevant to coaches only and the results of this questionnaire are shown in Figure 8. The questions were designed to collectively obtain information on the aspects being evaluated in the user assessments. These questions resulted in a large amount of quantitative data which users provided by completing an online questionnaire survey. There was no direct relationship between the users and authors and because the questionnaires were answered anonymously there was a good environment for users to give a critical evaluation of the overall system.

1. Learning to operate Match Point is straightforward.

2. Exploring new features by trial and error is straightforward with Match Point.

3. Match Point can reliably detect specific tennis events, which are queried by the user.

4. Match Point's Query Court panel is efficient at finding strokes played from a given region of interest on the court.
5. I found event retrieval easy with match Point.
6. It is easier to visualise tennis events using Match Points timeline control, game bar and event tick, than with the Dartfish application.
7. I prefer to use Match Point instead of Dartfish for tennis video analysis.
8. Using the system would improve my performance.
9. Using the system would enhance my effectiveness on the job.
10. Using the system would make it easier to do my job.

7.4.1 Useability Evaluation

As an additional part of the user questionnaire, an evaluation of the user interface using Nielsen's Heuristic Evaluation was performed. Nielsen's Heuristic Evaluation is one of the most common usability heuristics for user interface design [23]. Six heuristics were selected for useability evaluation and these were deemed most relevant to the user interface. The experimental setup for this study was as follows: when each evaluator had concluded all their system training, evaluation exercises and were therefore familiar with the user interface, they were asked the following questions which were to be answered by applying a score of how true the statement is (0 = false, 5 = true). All ten users answered this questionnaire. The results are shown in Table 3 and discussed in the next section.

1. Visibility of system status. The system always keeps users informed about what is going on, through appropriate feedback within reasonable time.
2. Match between system and the real world. The system speaks the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. It follows real-world conventions, making information appear in a natural and logical order.
3. Recognition rather than recall. Minimize the user's memory load by making objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. Instructions for use of the system should be visible or easily retrievable whenever appropriate.
4. Consistency and standards. Users should not have to wonder whether different words, situations, or actions mean the same thing. Follow platform conventions.
5. User Feedback. The user receives appropriate system notification in response to user actions.

6. Help users recognize, diagnose, and recover from errors. Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution.

7.5 User Study Evaluation

Several experiments were used to assess individual system components. If the experiments were only examined on a small number of people the reliability of individuals could be questioned, so by increasing the number of testers to ten reduced the ability of single tester to have a significant impact on the final accuracy score. However, the testers were trained on how to use individual system components directly before the test, so that they were familiar with each component. All results for the three experiments are given in Table 2, where the mean accuracy in Table 2 was calculated by dividing the combined final scores of correct queries by the combined number of queries in the test. Standard deviation was measured by taking a vector which consisted of each users overall result for a given experiment, then finding the standard deviation of this vector.

In experiment one, the events to be retrieved using the system were selected by observing what events coaches have manually annotated using Dartfish in the past. The system presented in this article can automatically annotate all the events used in this experiment. Therefore, the first benefit of using Match Point is that the system will reduce the time a coach will spend manually annotate videos of matches. The accuracy for Experiment 1 in Table 2 is a measure of how often users successfully completed each test within the allocated one minute time frame. When a user was unable to complete the experiment within the allocated time or had to ask for assistance the experiment was marked as a failure. Coaches unanimously agreed that automatically counting the frequency of stroke subcategories is a significant step forward for video coaching tools as it would simply take endless hours to manually tag this level of detail. This statistic has not been previously collected, to the best of the authors' knowledge. For example, the frequency of T, body or wide serves performed by a specific player has been identified as an interesting statistic by the system users because it allows coaches to find patterns in how often players are executing each style of serve. The number of times each serve type is executed within the deuce or add side is also recorded, as baseline positioning whilst serving has been highlighted as an interesting statistic by the coaches who were interviewed during requirements gathering.

Experiment two evaluated the User Query Panel, which allowed users to build queries of a particular stroke, executed from a specific region of interest on the court. If the user correctly constructed the query using the graphical tools and therefore successfully retrieved the relevant events after running the query it was deemed correct, otherwise the query would be incorrect. The user was allocated three minutes to construct each query. It was found that after sufficient training, coaches and players alike were easily able to build queries on the query panel and then playback the video of each returned result on the match timeline with ease. Since each result was represented by a vertical line on the match timeline, the user could then gauge how often each stroke was performed from the given region. The retrieval results in Table 2 highlighted some issues where the users did not retrieve the correct results and this typically occurred when a user did not draw the ball line along the correct plane. This article does not perform any user evaluation of the Virtual Rally Simulator though this is targeted for future research, however the authors have previously published ball detection accuracy results in [16].

Experiment	**No. Events**	**Mean Accuracy**	**Standard Deviation**
1	5	.83	9.1
2	3	.77	12.3
3	5	.74	14.1

Table 2: Accuracy of retrieval using the Match Point system

Heuristic	**Score**
1	80%
2	90%
3	95%
4	80%
5	50%
6	40%

Table 3: Nielsen's Useability Evaluation

The event retrieval task in Experiment Three highlighted that the Match Point system was designed for inter and intra match analysis, whereas Dartfish was not, as new Dartfish users struggled to load different matches with Dartfish. The system which was presented in this article has several features which make it more attractive for video retrieval, such as the easy-to-use time line, the game boundary marker and the vertical line which represents an event along the match timeline and users have reflected these observations with the user questionnaire. To obtain accuracy scores for Experiment Three in Table 2, users were allocated one minute to retrieve each event using Dartfish and if they were unable to complete the experiment within the time frame or required assistance, the test was recorded as a failure. Users who were familiar with Dartfish passed the experiments with ease, but new Dartfish users, who had received the same amount of training as was granted to Match Point's training exercises, struggled with useability issues, such as loading the events of match for the first time. The accuracy of event retrieval was higher for Match Point that for Dartfish as was highlighted in Table 2 and this result can be attributed to Match Point's direct function as a Tennis event retrieval system.

The user questionnaire results in Figure 8 conclude that coaches, some of whom are Dartfish experts, found Match Point significantly better for event retrieval. All users preferred Match Point's user interface over the leading video analysis software for sport. However Match Point's user interface was designed specifically for tennis, while Dartfish was designed for all sports. As the evaluation questionnaire results in Figure 8 highlighted, users found that using Match Point was more straightforward with the customised layout of events. What was also encouraging was the discovery that all users were able to build informative queries such as those in Experiment One and Two after only a short duration of system training and the accuracy in event retrieval is shown in Table 2.

The useability evaluation in Section 7.4.1 assessed the user interface. In this experiment six relevant heuristics were selected and each user completed the evaluation after using the system. The scores obtained from the first four heuristics are encouraging, however the low scores for heuristics five and six can be attributed to the system being a prototype and therefore it will be a future work to improve user feedback and error messaging. Improvements in these areas would significantly help the system to become more acceptable to the users in a production environment and the findings of this experiment are helpful for future work.

7.6 Tactical Analysis

An additional evaluation of the tactical analysis was conducted to highlight what coaches can learn from Match Point that may give them a novel insight. Since this system has the ability to record every stroke sub category and also records the location where each stroke was played, along with the ball direction of the stroke, this information can be used over multiple matches to gain insightful statistics on a given players tactical patterns. Example findings which were made by system users were to highlight where a given player has missed a high number of first serves during the first game of a match. Another tactical statistic was the ability to observe that one of the advanced players overuses the Wide serve from the deuce side of the baseline. This would give an opponent a tactical edge because it would allow them to stand in a more appropriate serve receive position and allow them to focus their attention on seeking visual cues that would confirm earlier where the ball was being served to.

8 Discussion

This research aimed to explore the effectiveness of a system to automatically detect tennis events using visual sensors. During the course of this article, a subset of tennis events were identified which can be automatically indexed using three low cost cameras. An evaluation of the accuracy of these event detectors has found them to be highly accurate at detecting each event. A secondary aim of this article was to evaluate the benefit of an event retrieval system for tennis coaches. The coaching system which is presented in this article gives coaches an extra insight into tactics and analysis and this comes at a low cost with minimal infrastructure, unlike existing instrumented coaching systems which

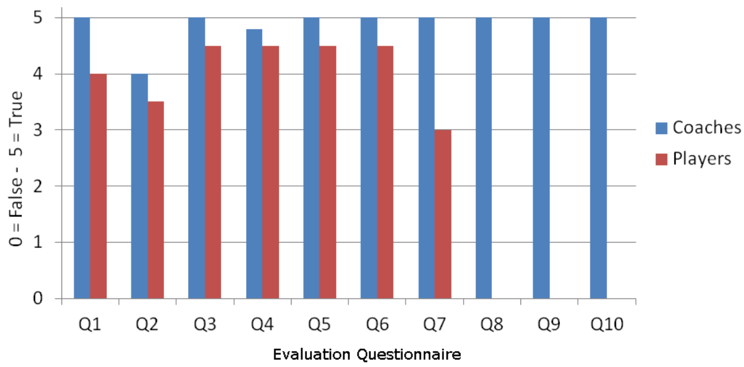


Figure 8: User study with six coaches and four players. Z axis values: 0= false, 1 = almost false, 2 = weak false, 3 = weak true, 4 = almost true, 5 = true

require a large amount of expensive infrastructure and cannot automatically index full matches. The hardware cost of the infrastructure used in this study was approximately 2000 euros and it takes the system on average 120 minutes to fully index 60 minutes of data on a single PC equipped with an Intel Core 2 Duo Processor. Through interviews with coaches, it was found that coaches can spend 3 to 5 hours manually editing a single tennis match using existing coaching software tools. Video coaching systems such as Dartfish and others require no infrastructure, but they do place a heavy burden on users to manually edit video, which is extremely time consuming and tedious. Many of the events inferred by this system can only be realistically indexed with automatic event detection techniques, as it would require an enormous amount of video editing to manually index events such as each stroke sub category by a given player and from what location it was played, for example. Further accuracy in event detection may be possible by identifying all of the events that were erroneously identified and determining if more biomechanical-based models would be more effective.

Coaches have specified a desire to perform real-time feedback and it is an aim to achieve this in future work. Existing instrumented coaching environments, which do provide real time feedback, cannot automatically index the level of detail which the system presented in this article can index. Existing visual coaching tools do provide the facilities to manually index any level of detail, but since manual editing is necessary, real time feedback is not possible.

While this system does not automatically detect every event in which a coach is interested, it does detect a large number of interesting events which enhance a coach's ability to analyse a match and it is true that this system could be merged with existing video coaching solutions to provide a semi-automatic coaching system. In this way, Match Point would automatically index all the events in Section 4 and then users could then manually index extra events, therefore reducing the time spent manually editing video. Coaches have expressed an interest in automatically inferring the scores and merging this information with the existing events. For example, when a rally is played back a coach would be informed of the score before the rally and the score after the rally. Through the investigations held, coaches have stated that knowing the score when a point is won or lost, would add an extra insight, as player decision making during a crucial rally exchange would be more important than a rally at the beginning of a set, for example. In fact, it would be highly desirable for future work to be able to determine the effectiveness of each stroke rather than simply the outcome (win/lose) of a collection of strokes i.e. a rally. Finally, minimal infrastructure and the ability to tactically analyse multiple matches without manually editing video, along with the low costs associated with this system make this solution valuable for coaching.

9 Conclusion

A comprehensive automated visual analysis system was presented. It was agreed by the tennis coaches that they prefer the Match Point system as an event retrieval interface when compared to a leading state of the art sports coaching software, as was proved by Question 7 in the questionnaire (Figure 8). The experiments have also proved that Match Point can infer knowledge which is simply not possible with manual annotation without applying significant human effort. For example, for every serve, the system can infer if it is T, Body or Wide. The system can also index every rally in the match, including the rally length. First serves made and first serves missed and return of first serves/return of second serves are also automatically indexed. This research has proved that automatic event detection is possible in racquet sports using visual sensors and that this process will significantly aid the coaching process as was found from the user study in this article.

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