3D Estimation and Visualization of Motion in a Multicamera Network for Sports

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***Abstract*—In this work, we develop image processing and computer vision techniques for visually tracking a tennis ball, in 3D, on a court instrumented with multiple low-cost IP cameras. The technique first obtains 2D ball tracking data from each camera view using 2D object tracking methods. Next, an automatic feature-based video synchronization method is applied. This technique uses the extracted 2D ball information from two or more camera views, plus camera calibration information. In order to find 3D trajectory, the temporal 3D locations of the ball is estimated using triangulation of correspondent 2D locations obtained from automatically synchronized videos. Furthermore, in order to improve the continuity of the tracked 3D ball during times when no two cameras have overlapping views of the ball location, we incorporate a physics-based trajectory model into the system. The resultant 3D ball tracks are then visualized in a virtual 3D graphical environment. Finally, we quantify the accuracy of our system in terms of reprojection error.**

I. Introduction

In professional sports broadcasts we are familiar with high-end camera technology being used to enhance viewer experience. High profile examples include the Hawk-Eye Officiating System as used in tennis, snooker and cricket. Whilst extremely valuable to the viewing experience, the cost of such technologies make them only feasible for high profile professional sports. Such technologies have also been adapted for sports video analysis and have been extensively used by coaches for the effective training of athletes. Presently, there are several commercial technological solutions for sports video analysis. However, these systems, again, tend to be expensive to purchase and run.

Recently advances in camera technology, coupled with falling prices, have meant that reasonable quality visual capture is now within reach of most local and amateur sporting and leisure organizations. Thus it becomes feasible for every field sports club, whether tennis, soccer, cricket or hockey, to install their own camera network at their local ground. By enabling sports video analysis with low cost camera networks, many local amateur clubs and sports institutions will be able to make use of these types of technologies. In these cases, the motivation is usually not for broadcast purposes, but rather for the technology to act as a video referee or adjudicator, and also to facilitate coaches and mentors to provide better feedback to athletes based on recorded competitive training matches, training drills or any other prescribed set of activities.

In this work, we focus using the videos obtained from such a low-cost camera network to track a tennis ball in 3D space during a tennis match. Although the obtained 3D ball tracking data could be used for decision making purposes, as in Hawk-Eye, we focus on its use as a low-cost tennis analysis system for coaching. This 3D data can be used for analysis purposes such as determining the speed of the ball over the net (a common tennis coach requirement), classification of type of shots played by the players, or to index the video frames and classify important events for coaching [1]. One of the main problems from using low-cost camera networks is that the individual camera data streams are typically not synchronized between sensors, as such a need for automatic video synchronization algorithms exists. In addition, the use of less expensive cameras can also result in significant optical distortion [2] being present in the video streams acquired, hence camera calibration of both camera intrinsics, as well as extrinsics, is essential. In this work, we also introduce a physics based model into our system, to predict the position of the ball when there is a lack of overlapping data from different camera views. Modelling of the ball trajectory is an essential part of this system as it provides continuity of the tracked features, leading to improvised tracking robustness.

The remainder of this paper is organized as follows: Section II outlines previous work in the area. A high-level overview of our system is provided section III. In this section, we subsequently describe the video analysis components that underpin the ball tracking techniques. In addition, this section provides details on both the physics based modelling that is incorporated into the system and on the visualization framework developed using OpenGL. Section IV provides quantitative experimental evaluation of our system in terms of reprojection error, and incorporates graphical results that provide visual feedback on the advantages of ball prediction in our system. Finally, conclusions and directions for future work are outlined in section V.

II. Related work

The work of [1] illustrates how a low-cost camera network can be effectively used for performance analysis if the tennis ball and player tracks from a match scenario are known. Our work extend that described by Aksay et. al.[3], where

978-0-7695-4629-2/11 $26.00 © 2011 IEEE
DOI 10.1109/IMVIP.2011.12

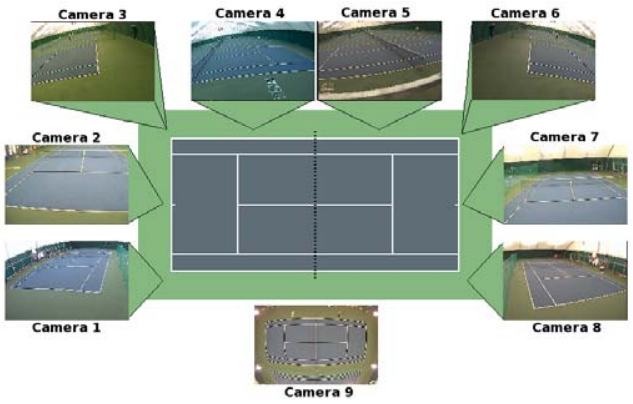


Fig. 1. Camera locations around the court.

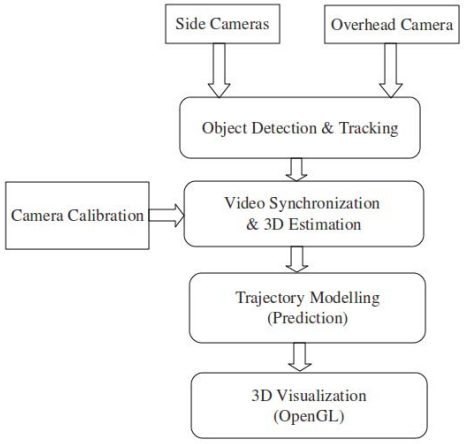


Fig. 2. Block diagram of the system.

techniques for 2D ball tracking, feature based automatic video synchronization and 3D estimation are described. We utilize the above mentioned techniques and improvise the overall quality of the system by developing our own algorithm for prediction in case of temporally missing points in a ball's trajectory. For this work. the dataset from the "3DLife ACM Multimedia Grand Challenge 2010 Dataset "[4] is utilized. This dataset includes 9 video streams of a competitive singles tennis match scenario from 9 IP cameras placed at different positions around an entire tennis court – see Figure 1. This dataset also includes chessboard images and 3D locations of some known objects in the scene for camera calibration. w

III. Algorithmic Design

Figure 2 represents our system at a block level. We use videos acquired from both side-view cameras and the overhead camera (see Figure 1) in the dataset for 2D ball detection and tracking, as explained in Section III-A. Camera calibration parameters are acquired from each individual camera using the Matlab camera calibration toolbox [5]. Once the 2D ball tracking information is acquired from each of the 2D camera views, each cameras video stream is synchronized with respect to overhead camera – see Section III-B. Once synced, the 2D ball tracking is extended into 3D space using the camera calibration information as explained Section III-C. A physics based trajectory model, which is required to provide continuity in obtained 3D data ball tracks, is then employed. The algorithmic description of trajectory modelling is provided in Section III-D. Finally, a virtual tennis court is created using OpenGL and visualized the motion of the ball, which is explained in detail in Section III-E.

A. 2D Ball Detection and Tracking

Previous work on object tracking, have included techniques such as frame differencing, optical flow, mean-shift and various other methods. However, in this work, we adopt a simple frame differencing and thresholding method. This approach is appropriate in the given context as the data set video sequences consists of a static background with the only moving objects being tennis ball and players. The process of extracting the ball trajectories begins with detection of ball *candidates* for every video frame, $S(n)$. This is a similar approach to the work one described in [3]. All of the moving parts of the frame that satisfy certain colour and size constraints are initially considered as ball candidates. In this approach, we firstly change the colour space of the image from RGB to YCbCr. Moving parts are then detected by utilizing the luminance (y) adjacent frame difference. For the n^{th} luminance frame, $S_y(n)$, we obtain the moving parts by thresholding the image, $M(n)$, calculated as:

$$M(n) = abs[S_y(n+1) - S_y(n)].abs[S_y(n) - S_y(n-1)] \quad (1)$$

where the . in the above equation represents element by element multiplication. In this way, the real moving parts of $S(n)$ are heavily emphasised in $M(n)$. Using 3 adjacent frames to detect moving parts in the middle frame, as in equation 1, is necessary step so that ambiguities in the location of moving parts are avoided.

To eliminate false candidates from the obtained locations, distance, colour and size constraints are applied. We first eliminate false candidates based on the colour information. The blue-difference, Cb, and red-difference, Cr, chroma components of the tennis ball are inspected over different frames and for different cameras. Empirical values for Cb and Cr are set and moving pixels outside this range are eliminated for consideration. Next, we apply a morphological dilation operation to enhance the size of the moving pixels and will result in blobs close to each other becoming part of one, larger, blob. Dilation is advantageous for identifying the blobs corresponding to players and tennis ball, as after dilation blobs corresponding to players will be much larger compared to the blobs corresponding to balls. Hence, by empirically setting a threshold value on the blob size, larger (player) blobs can be removed. The final constraint considered when eliminating false ball candidates is based on distance between tennis ball positions in two consecutive frames. A maximum distance is

(a) (b) (c)

Fig. 3. Results of Object Tracking using frame differencing and thresholding; (a) Original Frame; (b) Dilated Moving Pixels (c) Ball Blob.

set and any moving pixels outside this distance are eliminated. This way, only one coordinate (corresponding to centre of mass of tennis ball) is extracted for each frame. Figure 3(b) and (c) shows the processing results of the candidate detection technique on an input frame.

B. 3D Estimation and Video Synchronization

As the tennis videos in the data set are recorded at different frame rates, there is no guarantee that the individual video recordings were started at same time. In addition, as the individual sequence lengths differ slightly, some frames may have been dropped in each sequence during the recording process. This is typical of such low cost cameras. As such, there is need to synchronize these videos before the 2D ball tracks from multiple cameras can be used for 3D estimation. We implemented the feature based automatic video synchronization technique explained in [3]. This method requires that the estimated 3D coordinate features for each frame be known in order to determine the de-synchronized timing. Hence, its an inter-dependency problem where 3D ball track coordinates are required to synchronize the videos, and synchronized videos are required to calculate the accurate 3D coordinates of the ball tracks. In order to overcome this issue, we use the following technique. Firstly, we calculate a 3D ball trajectory point-by-point by triangulating [6] two 2D trajectories from the two videos to be synchronized. This 3D trajectory is then back-projected onto each one of the 2D camera views. Assuming that the camera calibration is accurate, back-projected 3D trajectories should be almost identical to the 2D original camera trajectories when the time shift used is close to the real de-synchronization of the videos. However, due to issues such as non-ideal calibration data and outlier 3D trajectories, the measure, $LM(\Delta)$, suggested in [3], is used to find out the best matching time shift Δ_{max}.

$$LM(\Delta) = \frac{L(\Delta)}{D(\Delta)}, \qquad L(\Delta) = count(||or - bp|| < T_L) \quad (2)$$

$$D(\Delta) = \frac{\Sigma||or - bp|| < T_L}{L(\Delta)} \quad (3)$$

where $||or - bp||$ is the Euclidean distance between the original point and back projected point and Δ is the tested time shift. $D(\Delta)$ is normalized Euclidean distance between points, calculated using only those points whose reprojected points are within distance of some empirically set value of T_L. The required time shift is

$$\Delta_{max} = \arg max(LM(\Delta)) \quad (4)$$

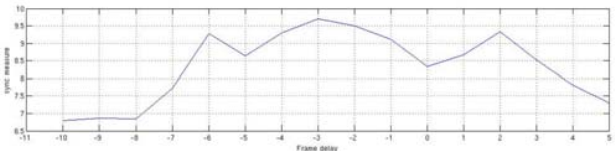


Fig. 4. Plot of $LM(\Delta)$ vs. Framedelay

Figure 4 shows the plot of $LM(\Delta)$ for different frame delays in a test scenario. We choose the value of frame delay that corresponds to the maximum value of $LM(\Delta)$. In this work, all the videos were synchronized with reference to the overhead camera, since this camera has a field of view covering the whole of the tennis court.

C. Robust 3D Tracking

A disadvantage of considering only two cameras for the 3D reconstruction is that we do not tend to get a continuous temporal 3D ball track stream, due to lack of availability of the synchronized 2D data in two views through all the frames. To overcome this drawback, we employed a robust 3D tracking method using the 3D coordinates obtained from different camera pairs at different points in time. We combine the tracking data from these multiple cameras to calculate a more stable, robust and accurate 3D ball trajectory. Let a 2D coordinate of the tennis ball at time instance, t, in the i^{th} camera view be $p_{2D,i} = [x_i(t), y_i(t)]^T$. We calculate 3D points using triangulation of the 2D points in each camera $(p_{2D,i})$ with the 2D point in the overhead camera (the 9^th camera) $(p_{2D,9})$, using backprojection technique described in [6]:

$$p_{3D,i} = triangulate(p_{2D,i}, p_{2D,9}). \quad (5)$$

The triangulate point from each camera pair, calculated at a given time instant, will correspond to one real-world 3D coordinate. Ideally, the acquired 3D coordinate should be identical across all camera pairs. However, due to several factors such as camera calibration errors, 2D tracker errors or triangulation approximation, each of the 3D points will tend to differ slightly. As such, some formal technique for combining these multiple 3D points is required. In this work, we use a weighted averaging to find a robust and accurate 3D point, p_{3D}, across all acquired 3D coordinates.

$$p_{3D} = \frac{\sum_i w_i * p_{3D,i}}{\sum_i w_i} \quad (6)$$

where w_i is the measure for the level of accuracy of each 3D point $p_{3D,i}$ and is calculated as the inverse Euclidean distance between the original 2D point $(p_{2D,9})$ and the back projected 2D point $(bp_{2D,i})$ on the 9^{th} camera view, as shown below;

$$w_i = \frac{1}{d_i} = \frac{1}{||p_{2D,9}, bp_{2D,i}||} \quad (7)$$

D. Physics Based Trajectory Modelling

In order to increase the continuity in the tracked features, the temporal prediction of the ball coordinates through times when no 3D ball information is available is required. This prediction is achieved by considering the trajectory of the ball to be that of a projectile. Projectiles are particles which are propelled under gravity through air, such as objects thrown by hand or shells fired from a gun. Typically, mathematics describe projectiles with both horizontal and vertical velocity components, and are subject to a downward vertical acceleration (i.e. acceleration due to gravity). To simplify the problem, a few assumptions have been made. Parameters like air resistance and ball spin, which would require modification in the modelling, have been neglected. We consider following kinematic equations of motion to predict the position of the ball in case of missing 3D points:

$$v = u + at \tag{8}$$

$$s = ut + \frac{1}{2}at^2 \tag{9}$$

$$v^2 = u^2 + 2as \tag{10}$$

where v is the velocity at any time t, u is the initial velocity, a is acceleration, and s is the distance travelled in time t. In our problem, as air resistance and ball spin are not considered, only the Z component of acceleration exists (-gravity), so the X and Y components of acceleration are set to zero. In our approach, we consider the X, Y and Z components of velocities separately and apply above equations to each component to predict position of the ball in case of missing points in ball trajectory.

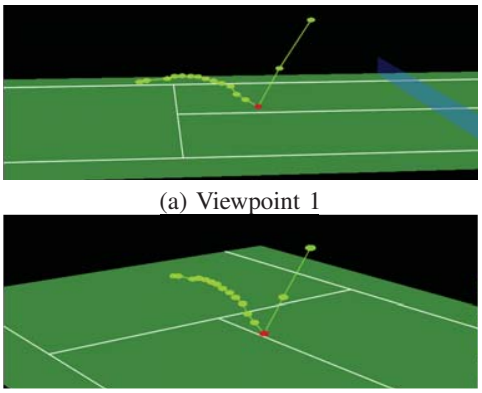
The coordinates are predicted using following steps: Say, frames i to $i + k$ require prediction

1) For the frame i with no 3D coordinate estimated, the X,Y,Z components of velocities are found out using tracked 3D points in frames $i - 1$ and $i - 2$.
2) Using this velocity information and the equations of motion, the 3D coordinate in the frame i is predicted.
3) Step 1 & 2 are carried out for all consecutive frames (up to frame $i + k$).
4) Predicted points are retained only if the predicted point in frame $i + k$ is within some tolerable distance of the estimated 3D coordinate in the frame $i + k + 1$.

Since the prediction model is very simple, the algorithm we developed predicts the co-ordinate of the ball incrementally. This approach reduces the accumulated error at the end of a trajectory.

E. Visualization Framework

If the developed algorithms are to be effectively used for performance analysis by coaches or as a decision making tool, a 3D graphical user interface (GUI) is essential, as the visualisation makes the system more intuitive and appealing. We have developed a GUI using OpenGL [7], one of the most widely used and supported 2D and 3D graphics application programming interfaces (APIs). It is hardware independent and very portable, hence it can be widely adopted across many platforms. The developed visualisation includes virtual tennis court, with an interface for selecting different camera views and zooming features – see Figure 5.



(a) Viewpoint 1

(b) Viewpoint 2

Fig. 5. Visualization of ball trajectory from two different viewpoints.

IV. Experimental Results

To evaluate our approach, we quantify the accuracy of our system in terms of reprojection error, which is defined as the distance between the actual 2D pixel coordinates and the reprojected pixel coordinates calculated using L1 Norm.

TABLE I
Reprojection Errors

Camera Combinations	Reprojection Error
Camera 2 & 9	10.5891
Camera 4 & 9	7.2260
Camera 2, 4 & 9	12.8549

Table I shows the reprojection error obtained for different combinations of cameras used for 3D ball tracking (see Figure 1 for camera label positions). As the number of cameras considered for analysis increases, the number of tracked points also increases, but at the cost of reprojection error. Unfortunately, for the tracked points with inclusion of prediction model, the reprojection error can not be calculated since ground truth data for comparison of such points is not available.

A graphical representation of the tracking results obtained for various techniques is shown in Figure 6. In this figure, time is on the horizontal axis, and times at which the ball is tracked is highlighted with a horizontal line, with times when the ball track is lost (i.e. not tracked) represented by a gap. From this figure, we can see that with increasing the number of cameras for tracking, the continuity in the tracked features also increases (compare row 3 to rows 1 and 2). The second last row represents continuity when prediction modelling is included. We can observe that some of the gaps are filled after incorporating prediction in the system. The additional temporal segments of ball tracks, that were acquired solely by prediction can be seen in the final row of this figure.

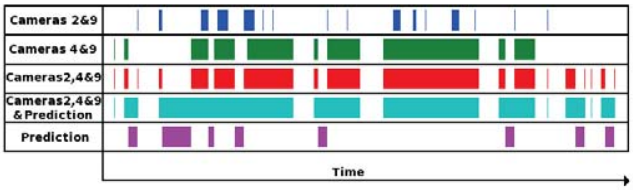
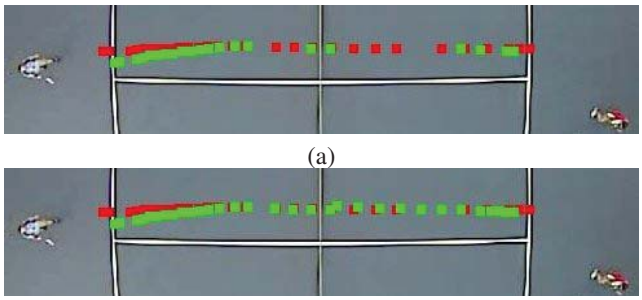


Fig. 6. Continuity of tracked features for different conditions



(a)

(b)

Fig. 7. Original (red) and reprojected (green) trajectories of the ball; (a) without prediction, and; (b) with prediction

The advantage of incorporating trajectory modelling is also illustrated in Figure 7, where trajectories with and without prediction are depicted. Notice how the tracked trajectory of the ball (in green) is increased in (b) when compared to (a).

V. Conclusions and Future Work

In this paper we presented algorithms associated with 2D and 3D object tracking and video synchronization. We also presented a basic, physics-based modelling technique designed to increase the continuity of the tracked features. We believe that, though the prediction model is very basic, it could be the first step towards development of a complex modelling system. In future work, an accurate modelling of the ball trajectory could be developed to ensure the continuity of the tracked features, by considering real-time scenarios like ball spin and air resistance.

Acknowledgements

This work is supported by Science Foundation Ireland under grant 07/CE/I1147.

References

[1] P. Kelly, J. Diego, P.-M. Agapito, C. O. Conaire, D. Connaghan, J. Kuklyte, and N. E. O'Connor., "Performance analysis and visualisation in tennis using a low-cost camera network," in *Multimedia Grand Challenge Track at ACM Multimedia*, 2010.

[2] G. Bradski and A. Kaehler, *Learning OpenCV-Computer Vision with OpenCV Library*, M. Loukides, Ed. OReilly Publications, 2008.

[3] A. Aksay, V. Kitanovski, K. Vaiapury, E. Onasoglou, J. D. P. M. Agapito, P. Daras, and E. Izquierdo., "Robust 3d tracking in tennis videos." in *Engage Summer School*, Sept. 2010. [Online]. Available: engage.miralab.ch/papers/

[4] C. O. Conaire, P. Kelly, D. Connaghan, and N. E. O'Connor., "Tennissense: A platform for extracting semantic information from multi-camera tennis data," in *DSP 2009 - 16th International Conference on Digital Signal Processing*, 2009, pp. 1062–1067.

[5] J. Bouguet, "Camera calibration toolbox for matlab." [Online]. Available: http://www.vision.caltech.edu/bouguetj/

[6] Y. Morvan, "Acquisition, compression and rendering of depth and texture for multiview video," Ph.D. dissertation, Eindhoven University of Technology, Eindhoven, The Netherlands, 2009.

[7] K. Group, "Opengl overview." [Online]. Available: http://www.opengl.org/about/overview/