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

Anil Kumar, P. Shashidhar Chavan, Sharatchandra V.K and Sumam David
National Institute of Technology Karnataka, Karnataka, India
Email: {anil3487, shashi3494, sharatkashimath}@gmail.com
sumam@ieee.org

Philip Kelly and Noel E. O'Connor
CLARITY: Centre for Sensor Web Technologies, Dublin City University, Dublin 9, Ireland
Email: {philip.kelly, noel.oconnor}@dcu.ie

***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 extracts 2D ball track data from each camera view, using object tracking methods. Next, an automatic feature-based video synchronization method is applied. This technique uses both the extracted 2D ball information from two or more camera views, plus camera calibration information. Then, 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, we also incorporate a physics-based trajectory model into the system to improve the continuity of the tracked 3D ball during times when no two cameras have overlapping views of the ball location. 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 we are familiar with high-end camera technology being used to enhance the viewer experience above and beyond a traditional broadcast. High profile examples include the Hawk-Eye Officiating System as used in tennis, snooker and cricket. Whilst extremely valuable to the viewing experience, such technologies are only feasible for high profile professional sports. Sports video analysis has also 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.

Advances in camera technology, coupled with falling prices means 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 prescribed set of activities.

In this work, we focus on tracking a tennis ball in 3D space during a tennis match using the videos obtained from low-cost camera network. Although the obtained 3D 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 ball track 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 cameras are typically no synchronization between sensors, as such a need for automatic video synchronization algorithms exists. In addition, the use of less expensive cameras also lead to the distortion [2] in the videos 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. Modeling 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. We give a high-level overview of our system in section III. In this section, we the subsequently describe the video analysis components that underpin the ball tracking techniques. In addition, this section provides details on physics based modeling that we incorporated and visualization framework developed using OpenGL. Section IV provides quantitative experimental evaluation of our system in terms of reprojection error, and graphical results indicating the advantages of prediction. Finally, we give our conclusions and directions for future work in section V.

II. Related work

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

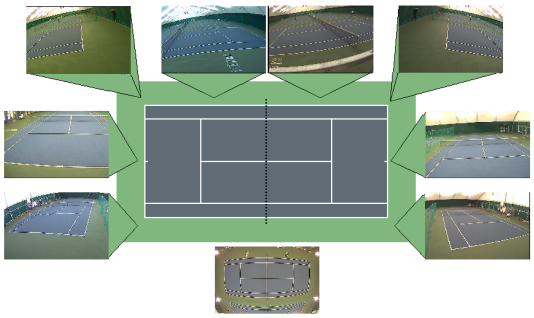


Fig. 1. Camera locations around the court.

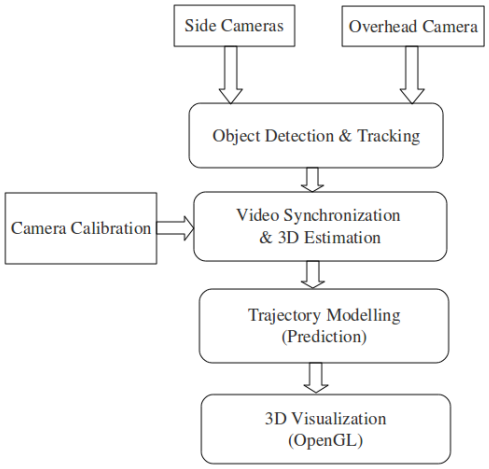


Fig. 2. Block diagram of the system.

own algorithm for prediction in case of missing points in the 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 Figure1. This dataset also includes chessboard images and 3D locations of some known objects in the scene for camera calibration.

III. Algorithmic Design

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

(a) (b) (c)

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

of the ball, which is explained in detail in Section III-E.

A. 2D Ball Detection and Tracking

Object tracking techniques include frame differencing, optical flow, mean-shift and various other methods. A simple frame differencing and thresholding method would suffice in the given context, since the data set provided has a static background with the only moving objects being tennis ball and players. In order to extract the ball trajectories, we begin with detection of ball candidates for every video frame $S(n)$. We use method similar to the one described in [3]. All of the moving parts of the frame that satisfy certain color and size constraints are initially considered as ball candidates. We detect moving parts by utilizing the luminance adjacent frames difference. For the n^{th} luminance frame, $S_y(n)$, we obtainthe 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 the false candidates from the obtained locations, distance, colour and size constraints are applied. We first eliminate false candiadates based on the colour information. The blue, C_b, and red, C_r, channel values of the tennis ball is inspected over diferent frames and for different cameras. An empirical values of C_b and C_r is set and moving pixels outside this range are eliminated. Next, we apply morphological operations (dilation) to enhance the size of the moving pixels, which otherwise, would be verydifficult to discrimanate between different objects. Dilation will also come into advantage in identifying the blobs correspondingto players and tennis ball, as 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, largerblobs are removed. The final constraint considered when eliminating false ball candidates is basedon distance between tennis ball positions in two consecutive frames.A maximum distance is set and any moving pixels outside this distance areeliminated. This way, only one coordinate (corresponding to center of mass of tennis ball) is extracted for each frame. Figure 3(b) and (c) shows the results of the above discussed techniques on an input frame.

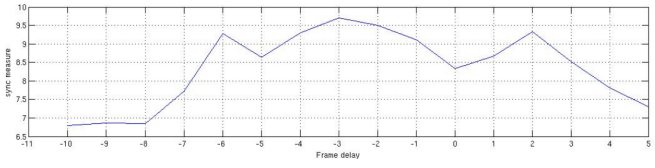


Fig. 4. Plot of $LM(\Delta)$ vs. Framedelay

B. 3D Estimation and Video Synchronization

Since the tennis videos in our data set are recorded at different frame rates,there is no guarantee of the videos being started at same time or that there will be no dropped frames through each sequence. As such, there is need to synchronize these videos before the 2D ball tracks from multiple cameras can be used for 3D estimation. As such, we implemented the feature based automatic video synchronization technique explained in [3]. This method requires estimated 3D coordinate features for each frame in order to know the de-synchronized timing. Hence, its an inter-dependency problem where 3D coordinates are required to synchronize the videos, and synchronized videos are required to calculate accurate 3D coordinate. We first calculate the 3D trajectories point-by-point using triangulation [6] of two 2D trajectories from the two videos to be synchronized. Then, the 3D trajectoriesare back-projected onto one of the 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}.

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

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

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

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

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 is that we dont 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 using3D 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, robustand accurate 3D ball trajectory. Let a 2D coordinate of the tennis ball at time instance, t, in 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 theoverhead camera (the 9^th camera) $(p_{2D,9})$:

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

The 3D points calculated at each time instance correspond toone real-world 3D coordinate and ideally all of them should be identical. However, due to several factors like camera calibration errors, 2D tracker errors ortriangulation approximation, each of the 3D points will tend to differ slightly, so some formal technique for combining these multiple 3D points is needed. in this work, we use a weighted averaging to find a robust andaccurate 3D point p_{3D}

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

where, w_i is the measure for the level of accuracy of each 3D point$p_{3D,i}$. w_i is calculated as the inverse Euclidean distancebetween 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 Modeling

Temporal prediction of the ball coordinates through times when no 3D ball information is available is necessary because to increase the continuity in the tracked features. This prediction is achieved by considering the trajectory of the ball to be a projectile. Projectiles are particles which are projected 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, few assumptions have been made. Parameters like air resistance and ball spin, which would require modification in the modeling, have been neglected. We consider following kinematic equations of motion to predict the position of the ball in case of missing 3D points:

$$v = u + at \quad (8)$$

$$s = ut + \frac{1}{2}at^2 \quad (9)$$

$$v^2 = u^2 + 2as \quad (10)$$

where v is the velocity at any time t, u is the initial velocity, a is acceleration, and s is the distance traveled in time t. In our problem, as air resistance and ball spin are not considered, only

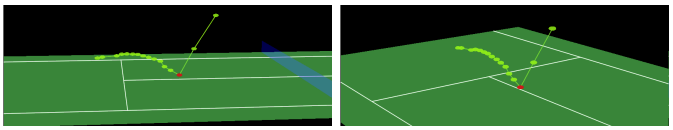


Fig. 5. Visualization of ball trajectory at two different viewpoints.

the Z component of acceleration exists (-gravity), so the X and Y components of acceleration are set to zero. We consider x, y and z components of velocities separately and apply above equations 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 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 $i+k+1$.

E. Visualization Framework

If the developed algorithms have 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 interface (API). It is hardware independent and very much portable, hence it can be used wide across many platforms. The frame work we developed is a virtual tennis court, with an interface of selectingdifferent camera views and zoom in features – see Figure 5.

IV. Experimental Results

To evaluate our approach, we quantify the accuracy of our system interms 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 tracking. 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 we do not have ground truth data to compare with.

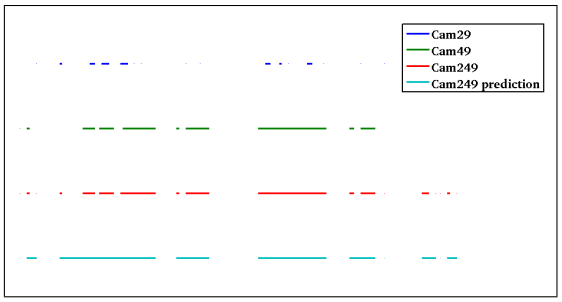
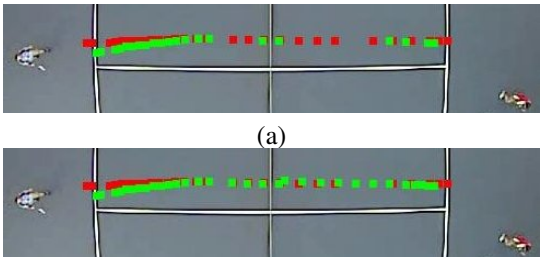


Fig. 6. Continuity of tracked features for different conditions



(a)

(b)

Fig. 7. Reprojected trajectory (green) of the ball; (a) without prediction, and; (b) with prediction

A graphical representation of the 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 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. The bottom line represents continuity when trajectory modeling is included. We can observe that some of the gaps are filled after incorporating prediction in the system.

This advantage of incorporating trajectory modeling can also be seen 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 & 3D object tracking and video synchronization. We also presented a basic, physics based modelling to increase the-continuity of the tracked features. We believe that, though the prediction model is very basic, it could be the first step towardsdevelopment 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 realtime scenarios like ball spin and air resistance.

Acknowledgment

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.

[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/