Tennis Court Mapping and Trajectory Optimization for Robotic Object Retrieval

Eng Sheh Ling and Edgar Scavino

Abstract - **This paper presents a real-time tennis ball retrieval system, using computer vision and a blind LEGO MINDSTORMS EV3 robot. Our system tackles the tennis ball retrieval issue of lacking ball boys, during professional or amateur matches. This system is able to identify the location of a tennis ball in the whole tennis court, to drive a robot along a fast trajectory while avoiding collisions with players. Semantic information on the court is captured using a webcam, which is located randomly near the external border of the tennis court with a flexible height. The image is then processed using a mapping algorithm to correlate pixels in the image and points on the actual tennis court. The camera location is evaluated by comparing the lines of the tennis court in reality and in the image. Feature extraction and computer vision techniques are used to detect the tennis ball and the player, which are found with margins of 4.5 cm and 45 cm respectively. To optimize the ball retrieval process, a genetic algorithm is applied to define the optimal trajectory with fulfilling multiple objectives for the robot to travel, arrive and retrieve a tennis ball. MATLAB is used to process image extraction and processing, to evaluate the mapping algorithm, and to define the trajectory optimization on the image of the tennis court.**

Index Terms - **Computer Vision, Genetic Algorithm, Tennis Court Mapping Algorithm, Trajectory Optimization**

I. INTRODUCTION

SPORT plays a vital role in human life because it not only helps us to stay healthy and fit but it also brings different people to play together. Tennis is one of the most popular recreational sports played at all levels of the society in the world. Playing tennis is a very demanding exercise as huge energy is used in playing on courts sized 78 ft. x 36 ft. Tennis is one among the few sports that in which a ball boy would be welcome to retrieve the spent balls quickly during a match, both at professional and amateur levels. During professional matches, a group of ball boys are squatting down next to the net on both sides of the court. To speed up the game and to relieve players from the need to go and remove spent tennis balls from the court, the ball boys must be alert, ready and quick to retrieve the ball each time an exchange terminates. This need becomes

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an issue for amateur players who lack the luxury of human or automated devices to perform this task not only during the match, but also during practice with only a limited number of balls. This task consumes time and energy and does not contribute to the match or to improve their skills, may cause backache due to frequent squatting or bending over, and may lead to possible injury to the players if they trip over the balls that are not retrieved from the court.

Currently, there is lack of commercially available devices to tackle these problems. So, it becomes advisable to apply robotic technology capable of performing the job of a human ball boy and to make it available cost-effectively to most tennis players. Intelligence, reliability, robustness, repeatability and efficiency are required in a robotic application that is able to interact with real-world objects when performing tasks as human being replacements. The system must have the ability to identify and recognize the spent tennis ball and every component at any point inside the tennis court, therefore an image acquisition device is needed to act as the eye of a robot. If the robot alone is unable to make intelligent decisions or lacks self-localization capabilities, the detection of the tennis court environment and the system control need to be performed separately [1].

Several models of tennis ball retrieval systems had been implemented using one or two image acquisition devices [1, 2]. For single camera utilization, the coordinates of the tennis court are identified with an omnidirectional or monocular vision approach, while the coordinate identification using two image acquisition devices is through stereo or binocular vision approach [3]. The position of these cameras is fixed either on the robot or mounted above the playing surface of a tennis court with their optical axes perpendicular to the plane of the ground, which is also known as 'overhead camera placement'.

This application requires an intelligent robot to respond and acts in the environment involving not only static spent ball, but also moving obstacles, such as players, in order to avoid collisions. An overhead camera placement is a more tractable scenario than that of the camera placed on the robot, because it provides a fixed and holistic view of the court globally and the extracted images contain information [1] which allows the robot to constantly keep track of its own and any obstacle positions. A camera on the robot is only capable to observe the small portion of the court directly in front of it, making it impossible to continuously observe its localization and all the components on the tennis court as a whole [4]. In addition, the measurements, especially the velocity of the obstacle, are troublesome and prone to errors due to the local perspective of camera on the robot. A fixed overhead camera can eliminate these errors in the measurements as its placement allows the image pixels to match linearly the physical coordinates and

results in simpler calculations for mapping targets [4]. Both configurations have the disadvantage of inflexibility in the placement of the cameras as they need to be fixed at a required position. Accuracy in detecting the coordinates of the targets at specific locations is also impacted.

Although a flexible camera placement involves extra calculations for the determination of its own position, it is more robust and flexible for the users. Such flexible positioning is a novelty for tennis court applications and is presented in this paper. In addition, in order to achieve a fast, collision free trajectory for the robot to travel and reach the spent ball safely, a genetic algorithm approach [5- 8] was implemented.

II. METHODOLOGY

This research is divided into six major development phases, which are image acquisition, image digitalization, object detection, mapping algorithm and position of image acquisition device determination, trajectory optimization using Genetic Algorithm (GA) approach, and system implementation in a blind LEGO MINDSTORMS EV3 robot, which is as shown in Fig. 1(a). Fig. 2 shows a flow chart of the tennis ball retrieval monitoring system used in this project.

(a)

(b)   (c)

Fig. 1. The hardware used in this project. (a) LEGO® MINDSTORMS® EV3 Home Edition Robot. (b) Logitech Webcam C930e. (c) AB Bluetooth Wireless Remote Shutter.

A. Image Acquisition and Preprocessing

In this project, a Logitech Webcam C930e, shown in Fig. 1(b) was employed thanks to its high resolution and wide viewpoint covering the needs to capture images up to the corner of tennis court to have a clear identification of the components on the

tennis court. Besides, the webcam is used as location sensors for robot localization to determine its current position.

The webcam can be placed randomly near the external border of the tennis court. Its resolution and saturation are set to 2304x1536 pixels and 255, respectively, in order to have a clear and high amount of color quality image. In order to start the retrieve procedure, the button on the AB Bluetooth wireless remote shutter, shown in Fig. 1(c), is pressed. At this point, a static image of the tennis court is grabbed and sent to the computer to identify the position of the ball and the player.

The digitalization process converts the features of a captured image into a set of samples in digital form. The purpose of utilizing digitalization process is to detect and extract the information of every component on the tennis court, such as tennis balls, players, court lines and shadows in order to determine the positions of the components on the tennis court.

Common types of edge detection algorithms, such as Canny and Sobel, were tested to identify the most appropriate method to be used to search for the boundaries of the tennis court. Edge detection is the most common technique for detecting meaningful discontinuities in brightness or intensity value [9]. However, due to the geometry and white color of border lines in a tennis court, detection was obtained with a saturation threshold less than 0.55 and value threshold more than 0.78. The detection was followed by a Hough Transform on the binarized image to evaluate the line equations in the image.
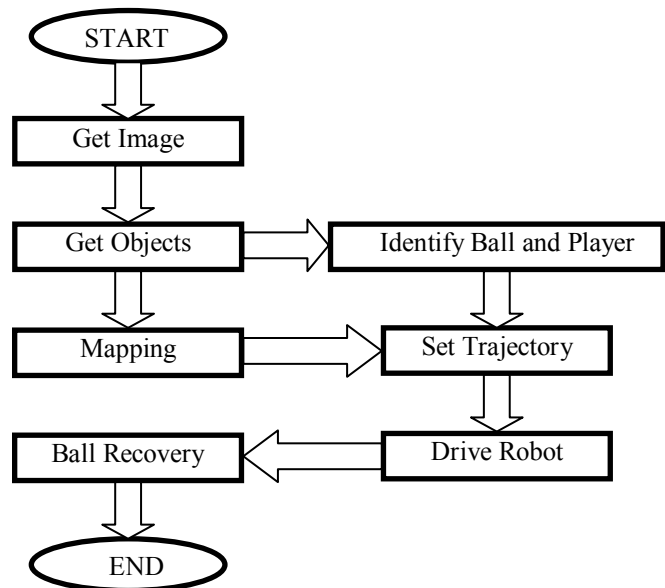

Fig. 2. Flow chart of tennis ball retrieval system

B. Object Detection

After obtaining a clear digitalized image, the system needs to identify the static spent ball and static player on the tennis court by processing this extracted image using image processing and computer vision techniques, respectively.

The most appropriate and logical method to identify the ball is based on color detection since all commercially available tennis balls have the same bright yellow tone. The tennis ball in the extracted image can be identified easily due to its contrast and

strong color. Shape detection alone cannot be used on here as there is the limitation of variable apparent size in a perspective image and the pixels of tennis ball are limited. Thus, the first step consists of searching the image for the exact color in HSV color space, which has very precise signals through intensity mapping. The threshold value for hue (H) is within the range of 0.16 to 0.2, saturation (S) is greater than 0.85 and value (V) is greater than 0.7. To detect the tennis ball effectively, another approach is added to measure the properties of image regions, which are eccentricity of the ellipse and centroid. Since tennis ball is a circle, its eccentricity is zero. Then, the center of mass of the tennis ball is used to specify its position in the image.

After identifying the spent tennis ball, the image is analyzed again for recognition of obstacles. The upright player in the image is detected using a pre-trained Support Vector Machine (SVM) classifier with Histogram of Oriented Gradient (HOG) feature extraction technique, available in Matlab Toolbox. Works in [10] have shown experimentally that this feature extraction technique is well suited for human detection.

C. Mapping and Webcam Position Determination Algorithm

In ideal pinhole photography, the real-world is represented onto the image plane via perspective projection [3]. In order to identify the locations of the tennis ball and the player in the extracted image, a mapping algorithm is developed to correlate pixels in the image and points on the actual tennis court by matching the lines of the court in reality and in the image. In this section, the geometric relations between the coordinates in object space and the projection place are presented. The overall relationship is depicted in Fig. 3.
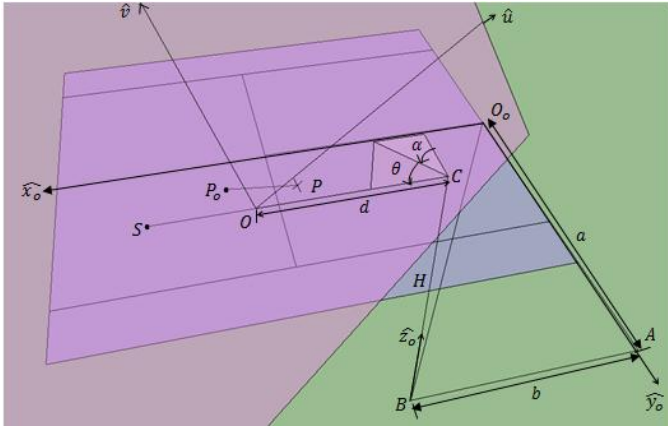

Fig. 3. Geometric relationship diagram of tennis court and the plane of projection from the camera.

The origin of the actual tennis court O_o is at the center point of the whole tennis court which is at the midpoint below the net. The camera pinhole has coordinates $C = (a, b, H)$ and is facing the court with viewing angles α and θ. The image plane is orthogonal at a distance d from the pinhole C and the pinhole projection is the origin in the image space. The horizontal axis $\hat{u}$ and the vertical axis $\hat{v}$ form the reference system in the image figure, in which the origin O is thus located in the center.

The equations of interest allow the calculation of the coordinates of a point $P_0 = (x_o, y_o)$ on the court once the coordinates of its image $P = (x, y)$ are measured. Intersecting

the view line CP_o with the image plane, the following relations are found:

$$x_0 = b + H \sin \alpha \frac{d + y \tan \theta}{d \tan \theta - y} - H \frac{\cos \alpha}{\cos \theta} \frac{x}{d \tan \theta - y} \quad (1)$$

$$y_0 = a - H \cos \alpha \frac{d + y \tan \theta}{d \tan \theta - y} - H \frac{\sin \alpha}{\cos \theta} \frac{x}{d \tan \theta - y} \quad (2)$$

The parameters a, b, H, d, α and θ can be obtained by matching the known positions of the tennis court side and base lines and their equations in the image, as well as from the equation of the horizon and the coordinates of the vanishing points. Assuming that the vanishing points are (x_{F1}, y_F) and (x_{F2}, y_F), the following parameters can be found:

$$d = \sqrt{-x_{F_B} x_{F_S} - y_F^2} \quad (3)$$

$$\tan \alpha = \frac{x_{F_S}}{\sqrt{-x_{F_B} x_{F_S}}} \quad (4)$$

$$\tan \theta = \sqrt{-\frac{y_F^2}{x_{F_B} x_{F_S} + y_F^2}} \quad (5)$$

In the image, let $y = m_1 x + q_1$ and $y = m_3 x + q_3$ be the equations of the external court side lines, and $y = m_2 x + q_2$ be the equation of the court baseline. Knowledge of the parameters in these equations allows the determination of the camera position $C = (a, b, H)$:

$$a = q_1 - H \tan \theta \cos \alpha - \frac{H \sin \alpha}{m_1 \cos \theta} \quad (6)$$

$$b = q_2 + H \tan \theta \sin \alpha - \frac{H \cos \alpha}{m_2 \cos \theta} \quad (7)$$

$$H = \frac{m_1 m_3 (q_1 - q_3) \cos \theta}{(m_3 - m_1) \sin \alpha} \quad (8)$$

D. Trajectory Optimization using Genetic Algorithm (GA)

The EV3 robot in this project is set to be initialized at a fixed location. The main focus to minimize the time required for the robot to retrieve the tennis ball can be achieved by running along the shortest linear trajectory. However, the shortest trajectory might not be applicable if an obstacle, such as the player, is present. To avoid collisions, a two meters circle around the player sets an off-limit area in which the robot is not allowed to enter. If the spent ball is inside this area, the margin is reduced accordingly. This constraint causes an increase in the trajectory length and the need to recalculate an optimal path. This can be solved using a Genetic Algorithm (GA) which dealt with three objectives to find an optimal trajectory, namely path length, off-limits penalty area and smoothness of the path.

GA is an evolutionary technique which combines couples of candidate solutions to form new ones, evaluates the qualities of each individual one and retains only the best ones. By operating multiple iterations, in the long term optimal solutions are found, which might not be the best but very acceptable anyway.

In this project, GA individuals are trajectories, all starting at the robot parking place (SP) and finishing at the ball position (TP). The coding is given by a sequence of eight intermediate points (IP) to be linked by path segments, as shown in Fig. 4.

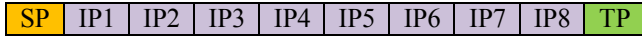| SP | IP1 | IP2 | IP3 | IP4 | IP5 | IP6 | IP7 | IP8 | TP |

Fig. 4. A trajectory individual with ten-point coding.

The crossover is carried out through the linear combination of randomly selected individuals with a variation of 20%. The mutation is made through the changes of one coordinates of a point on the trajectory with a variation of 10%. The GA cost function is defined as a weighted sum of trajectory length L, penalty for nearness to the player N and trajectory smoothness M, determined by the maximum distance between each two discrete points in order to have equal spacing between couples of consecutive points:

$$L = \sum \sqrt{(X_{i+1} - X_i)^2 + (Y_{i+1} - Y_i)^2} \tag{9}$$

$$N = max\big(40 - 10 \cdot distance(player, point)\big) \tag{10}$$

$$M = max\left(\sqrt{(X_{i+1} - X_i)^2 + (Y_{i+1} - Y_i)^2}\right) \tag{11}$$

The resulting cost is given by:

$$F_t = L + 20N + 30M \tag{12}$$

Typically, a population of 20 individual trajectories is considered, with the elitism of the two best individuals, and 200 generations are usually performed.

E. System Implementation in a Blind EV3 Robot

In the final phase, the developed tennis ball retrieval system in this project is implemented in the blind EV3 robot to validate its functionality. The tennis ball retrieval system interfaces with the EV3 robot, navigates it to approach and retrieve the tennis balls at a specific detected location on the court area through the optimal trajectory derived from the GA.

III. RESULTS AND DISCUSSION

This section outlines the simulated and experimental results from each stage with a discussion, analysis the accuracy of the results with respect to the actual tennis court, evaluates and validates the performance of the developed system.

A. Image Acquisition and Preprocessing

Prior to images acquisition of the tennis court, a Logitech Webcam C930e can be placed to any location allowing half tennis court to be captured inside the image. It is important to prevent the camera from laterally tilting, otherwise any image will have to be rotated to keep the horizon line in the image horizontal. Eight images were captured for experimental analysis with a variety of positions of ball and player.

An example of original image is shown in Fig. 5. The relevant objects to be identified are the court boundary lines, the ball to be retrieved, the tennis player and the shadows. The first step involves the identification of the tennis court lines and

the determination of the horizon and the positions of the vanishing points of the perspective image.

It was found experimentally that the common edge detection methods were unsuitable in this task due to the poor quality of court line detection. Moreover, the court lines detection usually resulted in a double edge, which would complicate the calculation of their equations in the image. Thanks to the fact that the court boundary lines are always white, the extraction of white color components proved to be the best solution, especially when a Hough Transform filtering for the detection of straight lines in the image follows the color detection. The results are shown in Fig. 6.
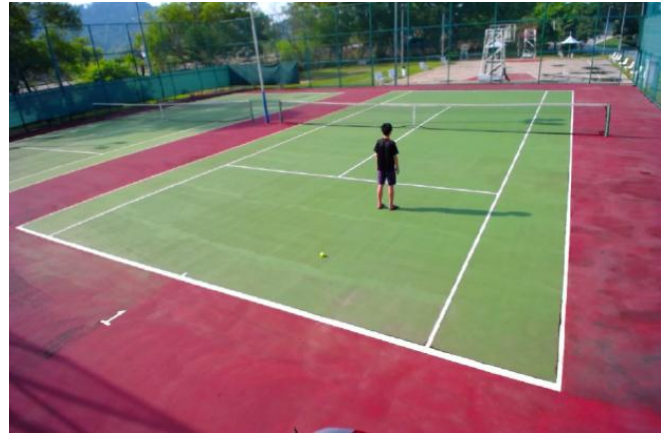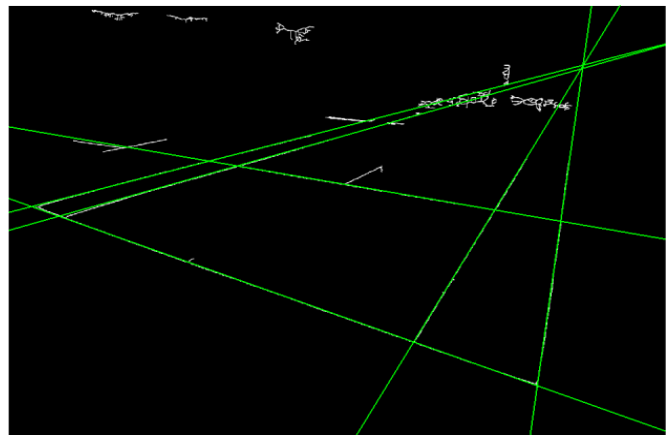

Fig. 5. Raw image from camera acquisition

Fig. 6. Court line detection using feature extraction and Hough Transform.

B. Mapping and Webcam Position Determination Algorithm

The equations of the court lines were used to find the positions of the vanishing points. The lines were separated into two groups, according to the sign of their slopes, then intersected 2-by-2. The sets of points thus obtained were averaged in order to define the best positions of the vanishing points. However, the mapping equations are valid only if the horizon line is actually horizontal, which might not be the case if the vanishing points do not have the same ordinate value. Consequently, we decided to rotate the raw image once of an appropriate value equal and opposite to the tilting of the line

connecting the vanishing points. These were recalculated by repeating the procedure described above.

In this example, $(x_{F1}, y_F) = (-2572, 614)$ and $(x_{F2}, y_F) = (898, 614)$. The viewing angles of the camera are found to be $\alpha = -59.4°$ and $\theta = 23.8°$, and the camera is located in $C = (15.486, 5.146, 3.357)$m with respect of the center of the court, as the reference system in Figs. 3 and 7.
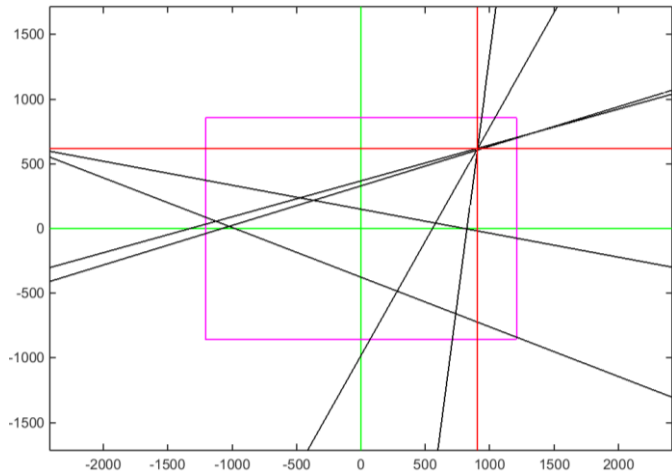

Fig. 7. Scheme of the ray lines (black) converging into the vanishing points (intersection of red lines). The magenta square defines the edges of the image, the green lines identify the center of the image and origin of image reference system.

C. Object Detection

The final goal in this project is the retrieval of the spent ball on the tennis court. Its detection, based on color and roundness evaluation, proved to be reliable and accurate. In this example, its position was $(10.38, 1.85)$ m. The second component to be detected was the player, in order to define a robot trajectory free from collisions. While the method described above might lack accuracy around the feet of the human figure, it proved to be very efficient also in presence of dark shadows. In this example, the position of detected player was $(7.64, 1.98)$ m, as in Fig. 8. The robot is identified by computer vision. Its starting position was $(0, 7)$ m, i.e. at the side of the net.
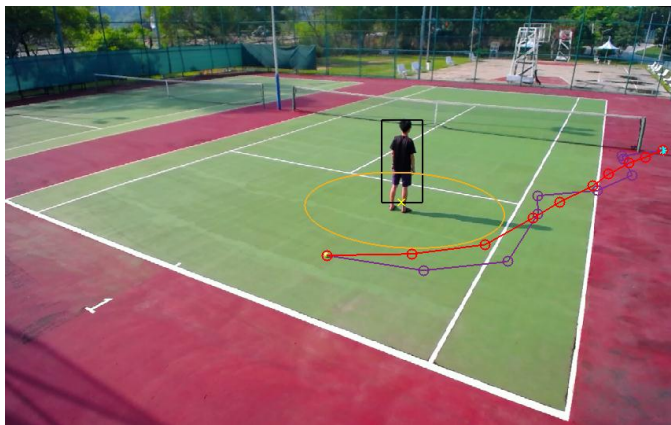

Fig. 8. Objects and paths identified inside the original image.

D. Trajectory Optimization using Genetic Algorithm (GA)

The path of the optimal trajectory was obtained via a Genetic Algorithm and its length was compared with the ideal linear trajectory between the robot parking place and the ball. The first GA generation path and the final one are represented in Fig. 8 in purple and red colors respectively. Their lengths are 13.00 m and 11.90 m and moreover the final path is much smoother, thus helping the robot into a regular motion. For comparison, linear distance is 11.55 m. In case sharp angles are still present in the final path, further smoothing is applied.

E. Detection and Measurement Analysis

Eight images were captured in an actual tennis court with different positions of camera, ball and player, in order to evaluate the accuracy of the identification and mapping algorithms. The results are presented in Figs. 9 and 10.
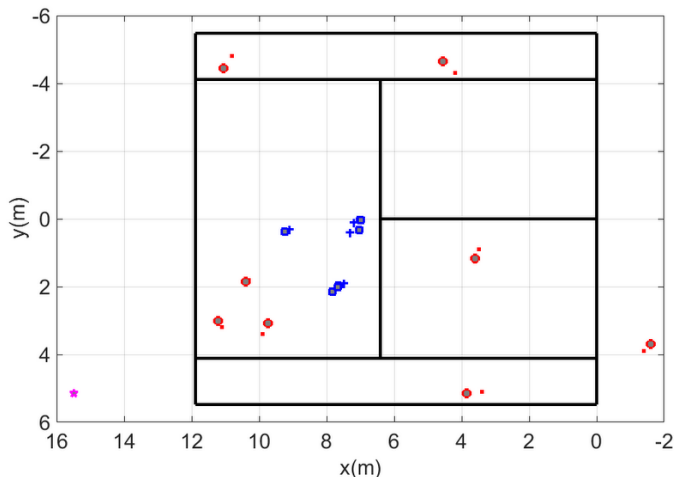

Fig. 9. The camera location (magenta pentagon), actual (.) and measured (o) locations of detected tennis ball (red), and actual (+) and measured (□) locations of detected player (blue) are obtained in eight different image sets.
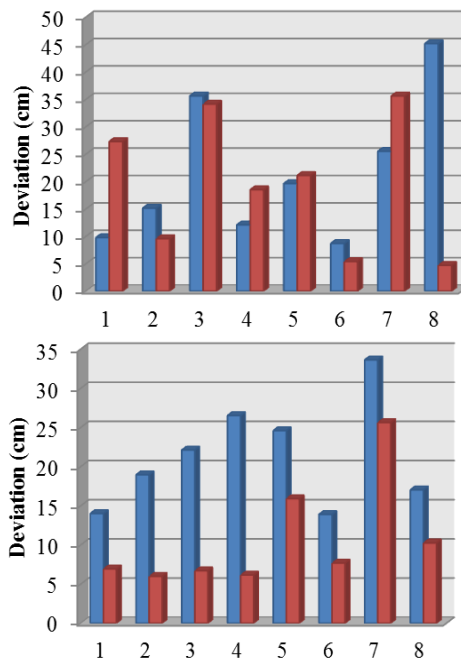

Fig. 10. Bar graphs of deviation in cm (x in blue, y in red) between measured and actual coordinates of (top) tennis ball and (bottom) player.

The mapping and tennis ball detection algorithms were more accurate and effective if the webcam was placed near to the tennis court due to increased image resolution. Far distance might reduce the pixel count of the tennis ball. A low cost image acquisition device can be used if it is placed at short distance next to the court.

F. Tennis Court Testing of Robot Motion

The robot motion was tested in an actual tennis court, in order to verify the accuracy of the adherence to a specified trajectory. A typical result is shown in Fig. 11. The robot reached each point numbered 1 to 6, grabbed the ball which was located at point 5 and sent to point 6.
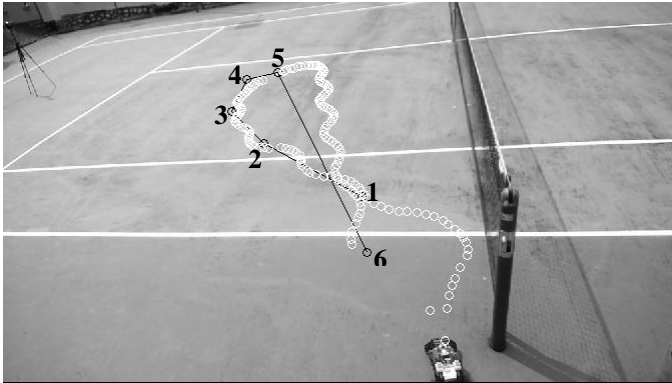

Fig. 11. The actual trajectory of the robot is identified by the sequence of white circles. In point #5 the ball was placed, then retrieved and sent to point #6.

In order to avoid a difficult wheel speed calibration, the EV3 robot was driven by a PID controller on the power of the motors, in which the input error was obtained by image processing. There was no need at this point to convert the pixel coordinates of the positions of ball and robot into the actual positions via the described mapping. The difference between the velocity vector of the robot and the direction towards the following point was evaluated and fed to the PID, until the robot reached a 30 pixel neighborhood of the point, then the next point became target.

During its motion along the specified trajectory, the location of the robot was tracked in the image in real time by means of a modified standard MATLAB example, capable of tracking multiple objects in motion. We determined that the best results in terms of detection efficiency were obtained with grayscale images. The position of the robot was calculated once every 30 ms, which correspond to the camera frame grabbing. The direction of the velocity vector of the robot was taken as the difference between two consecutive positions in the image.

IV. Conclusion

In this work, a variety of positions of tennis ball and player were detected using feature extraction and computer vision techniques in eight captured images in a real tennis court. The developed mapping algorithm precisely located the court lines and measured the position of ball and player with deviations of 9 cm to 45 cm in x and 4.5 cm to 36 cm in y. A Genetic Algorithm was used to find optimal paths for the robot to travel quickly from its fixed starting point to the ball position without colliding with the player. Tennis court testing showed that the robot could retrieve the tennis ball after following a given trajectory. Future work will focus on increasing the robustness of the movements of EV3 robot and on code integration of both robot controlling and image processing.

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