REPUBLIC OF TURKEY

AKDENIZ UNIVERSITY

DEVELOPMENT OF A BALL TRAJECTORY AND STROKE PREDICTION SYSTEM FOR TABLE TENNIS ROBOT BASED ON MACHINE LEARNING

Mehmet Fatih KAFTANCI

INSTITUTE OF NATURAL AND APPLIED SCIENCES

DEPARTMENT OF COMPUTER ENGINEERING

MASTER THESIS

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This thesis unanimously accepted by the jury on 01/07/2021.

Prof. Dr. Melih GÜNAY (Supervisor)
Asst.Prof.Dr. Özge ÖZTİMUR KARADAĞ
Asst.Prof.Dr. Taner DANIŞMAN

ÖZET

MASA TENİSİ ROBOTU İÇİN MAKİNE ÖĞRENMESİ TEMELLİ TOP YÖRÜNGESİ VE VURUŞ NOKTASI TAHMİNİ YAPAN SİSTEMİN GELİŞTİRİLMESİ

Mehmet Fatih KAFTANCI

Yüksek Lisans Tezi, Bilgisayar Mühendisliği Anabilim Dalı
Danışman: Prof. Dr. Melih GÜNAY

Temmuz 2021; 30 sayfa

Bu tez çalışması, masa tenisi sporunda oyun içerisinde atılan bir topun yörüngesinin en ekonomik yolla tahmin edilmesi için kullanılacak metod ve dataset bilgilerini içerir. Profesyonel/yarı profesyonel masa tenisi oyuncuları için en önemli sorunlardan biri, gelişmelerine katkıda bulunacak bir antrenör veya partner bulmaktır. Farklı oyun tarzlarına karşı beceriler geliştirmek için, bu tarzlardaki oyuncularla antrenman yapmak gerekmektedir. Diğer sporlara göre daha az popüler olması nedeniyle masa tenisi spor dalında bu fırsatı bulmak çok zordur. Bu sorunu çözmek için masa tenisi robotunun geliştirilmesi 1980'lerin sonundan beri yıllarca araştırma konusu olmuş ve bu alanda onlarca çalışma yapılmıştır. Tüm yöntemler için ortak sorun; topa iyi vuruş yapan masa tenisi robotu için uygun vuruş noktasını, raket yörüngesini, vuruş hızını ve açısını bulmaktır. Bu yöntemlerde ana hedef, doğru zamanda yörünge tahminini elde etmektir. Atak bir oyuncu için top uçuş süresi 200 ms'nin altında olabildiği için yörünge tahmini 100 ms'nin altında bitmelidir. Farklı yöntemlerle yapılan çalışmalarda bu soruna kesin bir çözüm bulunamamış olması tahmin algoritmasının daha ekonomik ve zamana duyarlı olması gerekliliğini ortaya koymaktadır. Bu araştırma ile var olan çalışmalardaki metodlar incelenerek en ekonomik metod ve bu metodun üzerinde çalışacağı dataset yapısı kurgulanacaktır.

ANAHTAR KELİMELER: Yörünge Tahmini, Makine Öğrenmesi, Yapay Zekâ, Masa Tenisi Robotu

JÜRİ: Prof. Dr. Melih GÜNAY

Asst.Prof.Dr. Özge ÖZTİMUR KARADAĞ

Asst.Prof.Dr. Taner DANIŞMAN

ABSTRACT

DEVELOPMENT OF A BALL TRAJECTORY AND STROKE PREDICTION SYSTEM FOR TABLE TENNIS ROBOT BASED ON MACHINE LEARNING

Mehmet Fatih KAFTANCI

MSc Thesis in Computer Engineering
Supervisor: Prof. Dr. Melih GUNAY
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This thesis study includes the method and dataset information to be used to estimate the trajectory of a ball thrown in a table tennis game. One of the most important problems for professional/semi-professional table tennis players is to find a trainer or partner who will contribute to their development. To develop skills against different playing styles, it is necessary to train with players of these styles. It is very difficult to find this opportunity in table tennis because it is less popular than other sports. To solve this problem, the development of table tennis robots for years has been the subject of research since the late 1980s and dozens of studies have been carried out in this field. Common problems for all methods; is to find the appropriate stroke point, racket trajectory, stroke rate, and angle for the table tennis robot that hits the ball well. In these methods, the main goal is to get the trajectory prediction at the right time. As the ball flight time can be under 200 ms for an attacking player, the trajectory prediction must end under 100 ms. The fact that there is no definitive solution to this problem in studies conducted with different methods reveals the necessity of the prediction algorithm to be more economical and time-sensitive. With this research, the most economical method and dataset structure that this method will work on will be designed by examining the methods in the existing studies.

KEYWORDS: Trajectory Prediction, Machine Learning, Artificial Intelligence, Table Tennis Robot

COMMITTEE: Prof. Dr. Melih GUNAY
Asst.Prof.Dr. Özge ÖZTİMUR KARADAĞ
Asst.Prof.Dr. Taner DANIŞMAN

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Special thanks to my family for their patience, support and big love.

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TEXT OF OATH

I declare that this study "Development Of A Ball Trajectory And Stroke Prediction System For Table Tennis Robot Based On Machine Learning", which I present as master thesis, is in accordance with the academic rules and ethical conduct. I also declare that I cited and referenced all material and results that are not original to this work.

01/07/2021

Mehmet Fatih KAFTANCI

ABBREVIATIONS

ITTF : International Table Tennis Federation

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1. INTRODUCTION

Table tennis is a sport played with at least two people, training and especially finding a suitable partner remains an unsolved problem for those who do this sport. Like in every sports branch, being able to do sports professionally in table tennis, being a team player, or even being a national player requires going through serious stages and systematic training. If such training starts at a very early age, it is possible to achieve success depending on the skill and determination of the athlete. While there are systematic training and sports clubs even for preschool children in popular branches such as football and basketball, it is not possible to find these opportunities in many countries including our country, even for adults for many other branches. Although there are a few sports clubs or sports centers providing training in the table tennis branch in some major cities, these are not sufficient for raising professional athletes. However, in many countries, especially China, Korea, Japan, and Germany, there are professional sports academies/clubs on this branch, and athletes are trained at a very young age. It is always a dream of amateur and professional athletes dealing with this sport branch to overcome this problem with a robotic system instead of finding competitors or coaches at the desired levels and abilities.

Artificial intelligence-supported table tennis robot is a subject that has been intensely studied for years to find partners and training, which is the main problem of everyone doing this sport. The absence of a project/product that has succeeded in this field yet remains a major deficiency. Some of the amateur and professional athletes following this branch meet their individual/partner independent training needs with ball launchers that are currently available in the market for training, although their names are called "table tennis robots".

The idea of table tennis robot has been the subject of research since the late 1980s and dozens of studies have been carried out in this field. Although the studies of the last few years have reached a certain stage with the development of technology (machine vision, supercomputers), it is still not a professional table tennis training and development tool.

In studies on this subject, simulation (Chen 2011, Nakashima 2014, Mülling 2010), humanoid robot (Yang 2011, Chen 2010, Sun 2009), real robot arm (Huang 2016, Liu 2013, Liu 2010, Koç 2016, Sun 2009) and the CNC (Zhang 2009, Zhang 2010, Zhang

2018, Ren 2013, Liu 2015, Wang 2015) system experiments have been carried out, but it has been determined that no project has turned into an industrialized product that will overcome the deficiency in this field. Also, in some of the studies carried out so far, the most important parameter of table tennis sport, the spin feature is ignored due to the difficulty of calculation and prediction. In recent studies, algorithms and systems have been tried to be developed by considering the spin factor (Tamaki 2012, Ren 2013, Nakashima 2014, Wang 2016, Zhao 2017). Forecasting algorithms are generally based on mathematical and physical calculations taking into account speed, spin, weather resistance, and friction coefficient of the table. It has been observed that some studies (Kuka, Forpheus), which are currently running but have not been put into mass production, are enough for newbies and for the players who plays for fun. The biggest deficiency of the studies is that after trajectory prediction, they all focused on stroke point estimation and/or return back the ball with the robotic arm. In other words, the main goal has always been focused on passing the ball other side or blocking. However, the robot's main goal should be developing the person who plays with. Also if we think even more futuristic, the robot should be coaching the player and analyze his/her game and reporting back shortcomings. Omrons' robot (Forpheus) version 5.2 does it even partially. It feeds back the movement that advised for player. After estimating the trajectory of the thrown ball, the system should calculate the angle, speed, and spin values by the data obtained from the estimated trajectory. Then the system should feedback on how this ball would return for an attacking game, defensive game, or training mode.

The robotic part (robotic arm or humanoid robot) is another study subject. However, the method developed as a result of this study and a table tennis robot, which is assumed to be the data set used, is expected to make the necessary trajectory prediction in the time that it should start moving. The focus of the thesis work is to convey the correct trajectory prediction information to the robot, which is supposed to exist now, as soon as possible. In very limited time estimations should be done by taking into account all details for the table tennis sport. Mathematical and geometric operations and progressive estimation methods were used on a large data set rather than physical calculations. Artificial intelligence and machine learning skills would be necessary for trajectory prediction and best return/stroke. The estimation of the remaining part of the trajectory will be calculated by machine learning based on the data obtained from previous trajectories. This prediction is not one-off, and it is constantly updated from the moment the ball starts moving from the opposite field to the position that the robot hits. The updated estimation data continuously flowing to the robot until the point of contact by starting the movement towards the average position with the first data for the robot's motion. Estimation of the correct point of contact and stroke motion/style is provided with the help of machine learning and artificial intelligence according to the estimated speed and spin data.

Different methods have been used at different steps on many different environments for development of a trajectory prediction system. The physical environment should be selected and placed in harmony with the methods to be used and the logic of the methods. As in many study examples, a stereo vision system was established and used in this thesis (Figure 1.1). Positioning the two cameras in accordance with the algorithms is another subject. In this study cameras are set up vertical 150cm above from table surface and horizontal 150cm away from table side in the net plane (that is, at the level of the middle of the table) to follow both sides of the table equally in order to facilitate position calculation. As mentioned above, time limit should be taken into account when choosing all the methods and algorithms to be used, considering that a fast hit reaches the counter-hit point in 108ms in an attacking game and the estimation process must be completed in 50-60ms. When comparing the methods, performance-time measurements should be made, and as long as the performance is at a sufficient level, the calculation should always be preferred in the shortest time.

Different methods have been proposed in recent studies. Common issue for all methods is finding the proper hitting point, racket trajectory, hitting velocity and angle for table tennis robot that strikes the ball back well. The main goal for all methods is obtaining trajectory prediction at the proper time. As a result of some test shots, it has been calculated that a shot by an attack player with a fast paddle from end of the table can reach to the counter hit point in an average of 108ms. Since the system is planned to be developed to complete the prediction in half of the total flight time, all calculations should be completed in 50-60ms. The development of a system suitable for a real-time game will only be possible with the use of hardware, calculations and algorithms to be completed in this period. Some of the methods are listed and examined in literature review section.

Figure 1.1. Environment

2. LITERATURE REVIEW

There are lots of studies done for the table tennis robot. Some of these studies dealt with all processes (including object detection, trajectory prediction, and the robot's striking point), and some studies specifically focused on a particular process. All of the methods we have reviewed have evolved over time with the experience of other researches. Researchers tried to find the best method for trajectory prediction in proper time. Some researchers used advanced physical formulas on dynamic features of the ball, some used machine learning on training trajectory data.

2.1. Methods Reviewed

Some of the methods reviewed in this research are listed below:

- Physics modelling by second order polynomial
- Regression Learning with experienced data
- Aerodynamics Model and Bouncing Model
- EKF (extended kalman filter) supported physical model
- Fuzzy rectification for spinning ball
- UKF (unscented kalman filter) on non-linear system and spin analyse with BP neural network
- ADM (Aerodynamics Model) and RRM (Racket Rebound Model) backward in time
- IELM (Improved Extreme Learning Machine) with non-massive data
- e-SVR (e Support Vector Regression) method
- Weighted least-square method

2.1.1. Physics modelling by second order polynomial

Zhang et al. [1] has proposed a method based on physics modelling of the ball without rotation. Second-order polynomials (1) are used to compute the x,y and z points of estimated trajectory on a given time.

$$\begin{cases} x = a_1^2 + b_1 t + c_1 \\ y = a_2^2 + b_2 t + c_2 \\ z = a_3^2 + b_3 t + c_3 \end{cases} \tag{2.1}$$

The coefficients a_1, a_2, a_3, b_1, b_2, b_3, c_1, c_2, c_3 can be computed via the least square method (LSM) with 3-D positions that calculated from the images captured by stereo-vision system.

Velocities (V_x, V_y, V_z) can be calculated via state vector :

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \\ \dot{V}_x \\ \dot{V}_y \\ \dot{V}_z \end{bmatrix} = \begin{bmatrix} V_x \\ V_y \\ V_z \\ -K_m \|\overrightarrow{V}\| V_x \\ -K_m \|\overrightarrow{V}\| V_y \\ -K_m \|\overrightarrow{V}\| V_z - g \end{bmatrix} \tag{2.2}$$

$$K_m = \frac{1}{2_m} \rho S C_D \tag{2.3}$$

Parameters used in physics model are in Table 1.

Time dependent positions and velocities can be predicted via iteration with

$$\begin{bmatrix} x_j \\ y_j \\ z_j \\ V_{xj} \\ V_{yj} \\ V_{zj} \end{bmatrix} = \begin{bmatrix} x_j - 1 \\ y_j - 1 \\ z_j - 1 \\ V_{xj} - 1 \\ V_{yj} - 1 \\ V_{zj} - 1 \end{bmatrix} + \begin{bmatrix} V_{xj} - 1 \\ V_{yj} - 1 \\ V_{zj} - 1 \\ -K_m \|\overrightarrow{V}_{j-1}\| V_{xj-1} \\ -K_m \|\overrightarrow{V}_{j-1}\| V_{yj-1} \\ -K_m \|\overrightarrow{V}_{j-1}\| V_{zj-1} - g \end{bmatrix} T_c \tag{2.4}$$

Table 2.1. Typical Values Of Parameters In The Physics Model

Parameter	Value
g	9.802 m/s^2
m	0.0027 kg
ρ	$1.29 \times 10^3 kg/m^3$
C_D	$0.4 \sim 0.5$
$\|\overrightarrow{V}\|$	$3 \sim 10$
C_L	$0.2 \sim 0.6$
r_b	0.02 m
ω	$0 \sim (10 \times 2\pi)\, rad/s$

2.1.2. Regression Learning With Experienced Data

Huang et al. [2] proposed a method based on constructing the ball map for trajectory prediction. initial state can be estimated after applying polinomial fitting [1] to the initial trajectory which came from vision system.
Rebound trajectory of the ball can be approximated by a parabolic curve and rebound trajectory pattern can be extracted using least squares method .

$$p_b(t) = \Phi(t)\omega_b, \tag{2.5}$$

$$\omega_b = ({\Phi_b}^T \Phi_b)^{-1} {\omega_b}^T p_b \tag{2.6}$$

With the regression learning method, entire ball trajectory can be estimated by experience data. How big is the experienced data-base, trajectory prediction by regression method improves.

2.1.3. Aerodynamics Model and Bouncing Model

Chen at al. [3] proposed aerodynamic model and bouncing model used together to predict ball trajectory. Aerodynamic model estimate the trajectory in flight time. Bouncing model used to calculate the velocity changes after bouncing.

In aerodynamic model, gravity (7), air resistance (8) and the magnus force (9) are formulated to obtain the trajectory for flying ball.

$$F_g = mg \tag{2.7}$$

$$F_d = -\frac{1}{8} C_D \rho_a \pi D^2 \|v\| v \tag{2.8}$$

$$F_m = -\frac{1}{8} C_m \rho_a \pi D^3 \omega \times v \tag{2.9}$$

In bouncing model, velocity and spin values after rebound can be computed if the incidence velocity, incidence spin, vertical restitution coefficient and friction coefficient of table are known.

2.1.4. EKF (Extended Kalman Filter) Supported Physical Model

Liu et al. [4] proposed an algorithm which combines the historical data and the real time information. Flying and rebounding model of the ball are formulated considered on spin.

EKF (extenden kalman filter) is used to estimate the status of the ball. Hitting point for robot can be calculated on a virtual hitting plane by iterations with thesis estimated ball status.

In this architecture system would keep gathering information and do prediction continuous till motion ends. This method is applied on different trajectories and the results are considered as ground truth.

2.1.5. Fuzzy Rectification For Spinning Ball

Ren et al. [5] informed a new algorithm that analyzes how the spinning effects on a flying ball for trajectory prediction. This algorithm is based on both model and experience learning. Due to both model based learning and experience based learning methods needs large sample of data and has prediction errors, this method proposed an algorithm that is combining these 2 method based on the error of the prediction results for the non-spinning ball and the real collected trajectory. This algorithm first predict the trajectory with non-spinning method then correct the errors with fuzzy rules like iterative method. Fuzzy rules are standard triangle membership functions applied to X, Ym and rot variables

2.1.6. UKF On Non-Linear System And Spin Analyse With BP Neural Network

Wang et al. [6] proposed a method based on applying Unscented Kalman Filter (UKF) to the non-linear model. Because of the Jacobian matrix calculation like complex operations Extended Kalman Filter (EKF) has intensive computation and less efficiency on prediction then UKF.

UKF is more suitable for real-time table tennis robot systems because of its accuracy and less time usage on computing.

UKF uses time dependent 9 dimensional vectors to represent state variables. Unscented Transformation (UT) is used as a method to calculate the statistics of a random variable in a non-linear transformation.

By constructing a BP neural network it is possible to decide the spin type. Three-dimensional velocity values for 5 virtual plane that comes from UKF filter as input values for the BP neural network. After data normalization and a method proposed for preventing over-fitting, spin type can be classified that comes from an output from BP neural network.

2.1.7. ADM And RRM Backward In Time

Nakashima et al. [7] proposed a method for trajectory prediction by solving ADM (Aerodynamics Model) and RRM (Racket Rebound Model) problems backward in time.

Finite Difference Method (FDM) is linearized from an approximated aerodynamics model (ADM) which has a Two Point Boundary Value Problem (TPBVP) that has to be solved. Also, TPBVP can be solved if striking point, landing points and angular velocity after striking is given.
In FDM time section is divided into subsections with the same interval and non-linear vectors are calculated by solving linearized ones iteratively.

2.1.8. IELM (Improved Extreme Learning Machine) With Non-Massive Data

Wang et al. [8] proposed a new method for trajectory prediction named IELM (Improved Extreme Learning Machine). In this method trajectory prediction accuracy is mostly related with identification and classification of spinning ball. So IELM is improved to predict spin value and classification with a non-massive data.

Primitive ELM (Extreme Learning Machine) is powerful on big data but this increases computation time. IELM is approximately 40 times faster than primitive ELM on non-massive data.

2.1.9. E-SVR (e Support Vector Regression) Method

Liu et al. [9] proposed a learning algorithm based on e-Support Vector Regression (e-SVR) to learn hitting policy that enables the robot to return the incoming balls to a desired location.

e-SVR uses the position and velocity of the incoming ball when it is passing through the specific virtual plane to represent the dynamic features of the ball. Virtual plane (state vector) is computed by interpolation of neighborhood locations of the ball around the virtual plane using a first-order polynomial of time in both x and y directions and a second-order polynomial of time in z direction.

2.1.10. Weighted Least-Square Method

Liu et al. [10] proposed Weighted Least-Square method to predict the trajectory of the flying ball by set of 3D locations and velocities that obtained from vision system.

GPU based stereo vision system is constructed to use multi-thread technology and speed up the image processing on blurred images.

Spatial coordinates of the ball calculated by using iterative procedure provided by OpenCV. Then trajectory predicted by fitting positions and velocities of the ball obtained from these coordinates to (10) using weighted least square method.

$$\begin{bmatrix} P_x(t) \\ P_y(t) \\ P_z(t) \\ v_x(t) \\ v_y(t) \\ v_z(t) \end{bmatrix} = \begin{bmatrix} P_x0 & v_x0 & 0 \\ P_y0 & v_y0 & a_y0 \\ P_z0 & v_z0 & g \\ v_x0 & 0 & 0 \\ v_y0 & a_y0 & 0 \\ v_z0 & g & 0 \end{bmatrix} + \begin{bmatrix} 1 \\ t \\ \frac{t^2}{2} \end{bmatrix} \tag{2.10}$$

2.2. Performace Analysis Of The Reviewed Methods

In this section a comparative performance analysis of the methods based on accuracy, time usage and relevance for a table tennis robot system that is suitable for professional table tennis training. Results of performance and analyses are presented in Table 2.2. Accuracy and time usage is the most important parameters to analyse a method. Because if accuracy is not enough to predict the hit point for robot system, ball van not be returned. On the other hand all computations, prediction and robotic arms movement to return the ball have to finish in a flight time of a flying ball in table tennis.

2.2.1. Accuracy

Some researchers suppose that hitting the ball and turning back it to the opponent side is a success and calculate the accuracy with returning percentage. Some suppose the distance from the predicted striking point to real striking point as accuracy.

2.2.2. Time Usage

Main goal for this research is finishing all computations and prediction in a very short time (50-60ms). Because if there would be a table tennis robot and we want it to train a real player, this robot system have to finish prediction in 50-60ms. Other computations, methods and systems would not be used in real time table tennis training systems. So the main thing is finishing every method or sub-method as quickly as possible. Time usage is determined as the time passed for a successful prediction or flight time of the ball that has been predicted well.

Table 2.2. Accuracy, Prediction Time And Results For Methods In Literature

Method	Accuracy	Time	Sol.
Physics modelling by second order polynomial	Average 6.5 mm	2658 ms	No
Regression Learning with experienced data	%96 Successful return	-	No
Aerodynamics Model and Bouncing Model	Less than 1cm	$\sim$ 1 second	No
EKF supported physical model	Accuracy increases approximately %20 after filtered	Time decreases approximately %20 after filtered	No
Fuzzy rectification for spinning ball	Left Rotation: 1-6 cm Right Rotation: 0.1-3 cm	-	No
UKF on non-linear system and spin analyse with BP neural network	X < 30mm Y<35mm Z<40mm	1 second	No
ADM and RRM backward in time	$\sim$ 0.05 cm	$\sim$ 0.63s	No
IELM with non-massive data (precision of identification on spin)	%83-%95	0.086-0.62 second	No
e-SVR Method	2-26 cm	0.44-0.53 s	No
Weighted Least-Square Method	0.5-3cm	-	No

3. MATERIALS AND METHODS

3.1. Materials

3.1.1. Machine Vision System

Two high FPS industrial camera with USB3.0 interface used for machine vision system. 4mm 1:1.8 lens mounted to the cameras. As in all the studies referenced in the literature review section, two cameras should be used for object detection and localization. In order to determine the location with the images taken from the machine vision system, the frames taken from the two cameras must be exposed at the same time. As mentioned before, considering that the flight is completed in a time of 108ms on an approximately 300cm trajectory in an attacking shot from an attacking player in a table tennis game, even 1ms difference between camera exposure times will cause a deviation of about 3cm. Since this deviation will be in the images to be used for position determination, it will cause more deviation for the location measurement to be determined in the geometric processes used in the determination of the position. In the shootings and stereo vision camera shooting trials as shown in Figure 1.1, it was concluded that it would not be sufficient to obtain simultaneous images from two cameras with a standard PC hardware. It has been understood that simultaneous camera exposure triggering mechanism called trigger should be used in order to make a healthy measurement. But in this research several manuel triggering has been tried to catch simultaneous frames from two cameras. Some shoots which are exposed from two cameras in the same milliseconds are recorded and used in algorithms for all trajectory prediction period.

3.1.2. Hardware For Computation

In this research, a computer with two USB3.1 ports, i7 processor, 2Gb external video card (Nvidia - Cuda supported) and 8Gb RAM memory was used to perform all operations from taking images via machine vision system to estimating the contact point of the ball on the table. With the help of C++ programming language and C++ compatible OpenCV libraries, object detection (Figure 3.2), object tracking and 3d position detection of flying ball operations are performed offline on this computer.

Since two simultaneous image capture processes were performed without a trigger system, the written codes could not be tested live at runtime. Video recordings where the simultaneous (same ms) exposures of the two cameras coincide were tested offline on the relevant algorithms.

As mentioned before, since all the necessary steps for estimation are expected to be completed in 50-60ms, the processes must be distributed simultaneously (multithread). On the other hand, the operation of the last algorithm required for estimation should be carried out simultaneously (multithread) over the detected points, which will not make each other wait.

It was observed that the operations completed using the OpenCV library on the CPU were 7-8 times slower than the same operations using Cuda and OpenCV on the GPU.

Figure 3.2. Object Detection Test Of Images From Machine Vision System

3.1.3. Environment

In order to estimate the ball trajectory for a real table tennis game (Ground truth), it is necessary to operate in an environment that complies with the environmental conditions of table tennis standards (ITTF standards). In order to provide such an environment, shots were made and measurements were taken with an ITTF approved table tennis table, ITTF approved net and ITTF approved table tennis balls in a large and closed (windless, temperature and humidity at room temperature) hall.

The images obtained from the first shooting attempts were not efficient for image processing and especially for object detection. It was understood that the reason for this was the light in the environment, and shooting attempts were made by increasing the ambient lighting. More reliable data could be obtained, especially from the image processing algorithms, in shooting trials and shootings made by amplifying the ambient light.

As in many study examples, a stereo vision system was established and used in this thesis (Figure 1.1). Positioning of the two cameras in accordance with the algorithms is very important due to the object positioning algorithm. In this study cameras are set up vertical 150cm above from table surface and horizontal 150cm away from table side in the net plane (middle of the table). It helps following both sides of the table equally in order to facilitate position calculation. As mentioned above, time limit should be taken into account when choosing all the methods and algorithms to be used, also object positioning should be finished as quickly as possible.

The Point T (zero point) for the x,y,z plane is accepted as 150 cm back and 150 cm left from bottom-left corner of table (where the shot is made) (Figure 1.1). And the location information, which was determined from the images of the ball captured by the stereo vision system, was recorded to the data set in millimeters (mm). The balls that do not touch to the table (opponent area) or are caught in the net are excluded from the data set, and only valid shots are accepted as ground truth data.

Since the frame (exposure) frequency of the camera is 4ms in the shots taken, approximately 50-100 frames can be captured, assuming an average of 200-400ms for a normal shot. For the fastest shots in attacking games, this time drops to 100 ms. In order to find the fastest shot to be captured by the camera, speed tests were also made with the attacking racket and rubber type, and the average of the offensive hits made from the starting point of the table was recorded as 108 ms.

3.1.4. Programming Language

C++ programming language is the most suitable programming language for this type of applications. C++ is a language which is closest to the machine language, it can be processed very quickly. It is compatible and running fast with Cuda and OpenCV libraries. And it also performs much better than other programming languages because it allows data transfer between different code blocks and threads through the use of pointers.

Graphical operations can also be performed more efficiently with C++ programming language too. For these reasons, the C++ programming language was used in order to get faster results in the methods in all the steps of our research.

3.2. Methods

3.2.1. Object Detection

Object detection is the first step in the table tennis ball trajectory prediction process. In this step, the position of the ball on the picture is determined by a series of processes on both images coming simultaneously from the stereo vision system. These procedures vary according to the methods. In this study, object detection was done with the help of OpenCV library. The raw image from the camera is first converted to HSV format (Hue-Saturation-Value)(Figure 3.3).

At this stage, minimum and maximum value ranges should be defined for Hue, Sturation and Value values in order to determine the pixels to be selected from the pixels in the image to be converted to HSV. In other words, determining in which range to separate the values of color saturation and light intensity. At the end of this stage, the pixels between the Hue Saturation and Value (light, brightness) values are revealed and the other parts are ignored. This is called background subtraction.

In the next step for object detection, Threshold Image is created. And detection is done with a function named HoughCircles in OpenCV library.

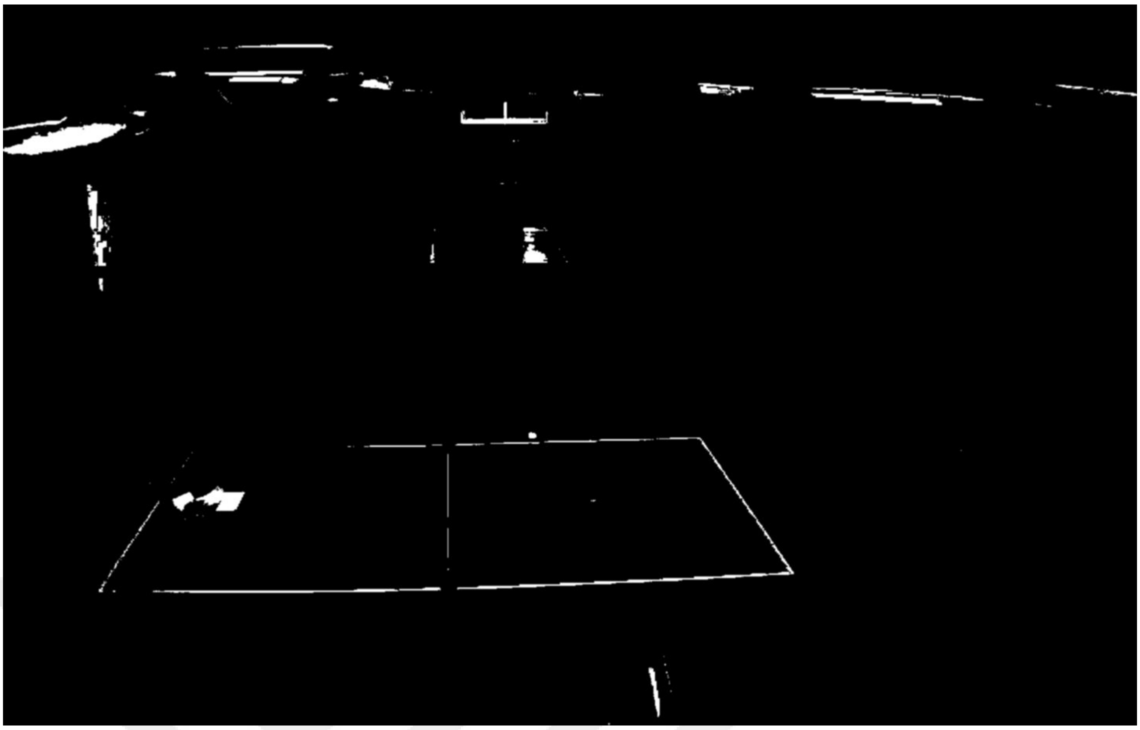

Figure 3.3. HSV converted Image Sample For Object Detection

As it mentioned before all methods and sub-methods should finish as quickly as possible. So it would be better to use primitive and raw C++ codes to finish the computation in less time. But in this research we had to use some ready functions like OpenCV to finish the project in proper time. It is planning to do these steps (just detection and tracking steps, other steps has raw C++ codes) with raw C++ codes in next studies.

It would always be better to find any way to minimize the overall time passed on computation. When any methods found or improved in terms of time constraint, without accuracy loss, system would get better and maybe would work with cheapest hardware.

3.2.2. Object Tracking

Object tracking is the second step for a trajectory prediction system of a flying ball. In this study, the OpenCV library was used directly to the images that comes from stereo vision system for object tracking at first.

But, after some tests, it was determined that using a part of the image instead of using the whole image from the cameras would be beneficial to reduce the time passed in the

Figure 3.4. Object Tracking On Cropped Image

object tracking method (Figure 3.4).

In this step, a logic is also applied to calculate how much of the picture will be cropped. First of all, considering that a fast shot captures approximately 30 frames during the total flight time (with cameras that have 4ms exposure time), and we aim to finish the prediction in half of this time, a total of 15 frames of footage must be processed until the estimation time. However, it is thought that it is more efficient to do computations in every two frames for system performance and reducing the computation times.

After detecting the object in the first frame, since the direction of movement of the ball is not known yet, a square cropping was applied in the second frame by centering the ball (detected in the previous frame). Considering that the ball travels approximately 240mm in 1ms in tests for the fastest shot, the number of pixels (that will take the ball to the center) calculated in the second frame will correspond to a maximum size of 240mm. A square shaped area is cropped on the picture and only this area is used for object tracking (Figure 3.5).

In the frames after the second frame, the clipped area is approximately 300mm from the ball to the direction of the movement. Since the direction of movement of the ball is

Figure 3.5. Object Tracking On Cropped Image For Second Frame

determined (the reason for taking 300mm, not 240mm here, is that the movement direction will not be fully linear due to factors such as spin and air friction, so there may be a slight margin of error) towards the direction of movement, a square section (Figure 3.6) will be taken and the ball will be tracked within this square.

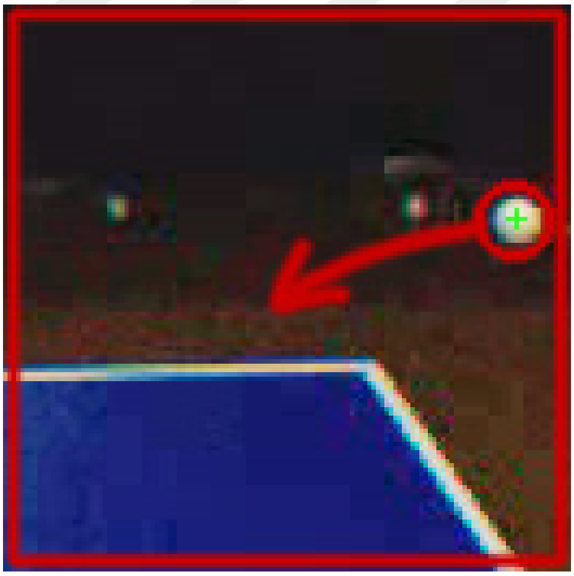

Figure 3.6. Object Tracking On Cropped Image After Second Frame

While these cropping operations are performed, the point where the ball is located on the basis of pixels in the entire image can be determined by keeping the location of the image in the variables where the cropping is made (Figure 3.4). In this way, the computation time is significantly reduced, since image operations will be performed on a part of the image, not the whole.

3.2.3. 3-D Positioning Of Flying Ball

Finding the position of the ball in 3D is normally a complicated and computationally intensive step. In order to complete this stage in less time, like other steps, location information was accessed with the simplest level of geometric calculations based on some reference points in our environment (Figure 3.7), and position information was obtained in less than 1ms.

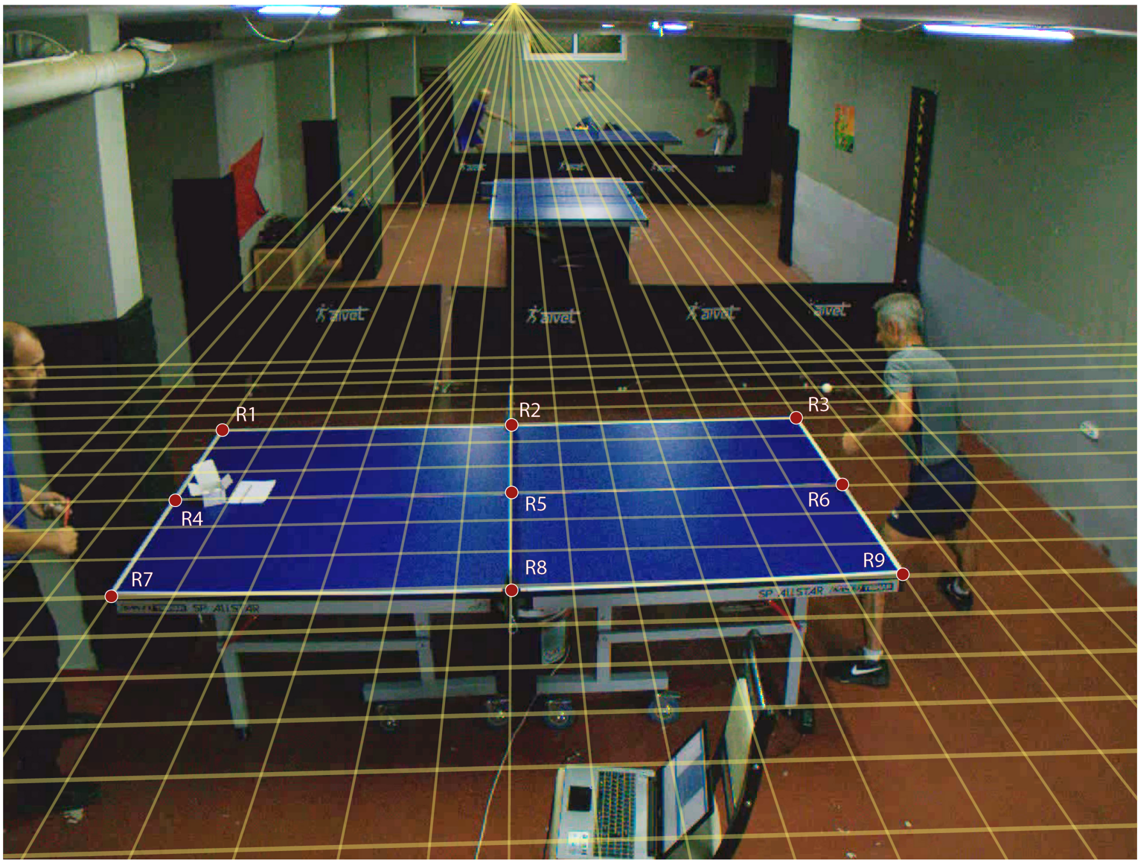

Figure 3.7. 3D Positioning And Virtual 3D space

Unlike other 3d position finding problems, a virtual 3D space environment has been created in our environment based on our fixed objects (especially the table) and fixed reference points (R1, R2, R3, R4, R5, R6) on table tennis table. On this virtual 3D space, it can be determined that the position of the ball in the image taken from each camera is in the direction of which point in the x-y plane according to the camera viewpoint. A virtual triangle (B-C1-C2 triangle) was created with the position (B) of the ball and these two new reference points (C1, C2), which are detected over two cameras, and the position calculation is based on this triangle. Since the ratio of the side B-C1 to the side B-C2 of the sides in this triangle is proportional to the distances of these points from the center line of the table. The ratio of these two sides and therefore the tangent value of the angle at point B can be found. Since the actual size of the C1-C2 line can be found from this virtual plane, the edges B-C1 and B-C2 can also be measured. The Z position of the ball can be found from the ratio of the length of these other two sides to the distance of the camera to these points (similarity of triangles). Since the height of the camera to the table is fixed and it is 1500mm, the position of the ball in 3 dimensions can be easily estimated by this Z point and the side lengths of the B-C1-C2 triangle.

Table 3.3. Position Information of A Shot In The Ground Truth Data

X Pos.	Y Pos.	Z Pos.
2675mm	1860mm	1814mm
2682mm	1990mm	1797mm
2689mm	2113mm	1775mm
2695mm	2230mm	1748mm
2701mm	2341mm	1713mm
2707mm	2447mm	1669mm
2713mm	2547mm	1615mm
2718mm	2642mm	1550mm
2723mm	2732mm	1472mm
2728mm	2818mm	379mm
2732mm	2900mm	1270mm
2737mm	2978mm	1144mm
2741mm	3051mm	999mm
2745mm	3121mm	833mm

Table 3.3 is a sample data set for 3d position of a flying table tennis ball.

3.2.4. Prediction Methods

There are three prediction steps for a real time playing table tennis robot trainer. Two methods are for Trajectory Prediction (first is before ball bounds second after bounds), and also there is a counter-shot prediction method.

Trajectory Prediction Method Before Ball Bounces In the first days of the project development phases, since there was no physical environment and stereo vision system for a real-time tests, a simulation environment that imitated the physical environment was created and virtual shots were made. In these shots, the physical impact forces were planned to create equal conditions in each shot. Thus, it was possible to work on table contact point predictions on a data set whose 3D position (x-y-z) information was ready.

Although many machine learning algorithms were tried with the data in the simulation environment, it was determined that the most efficient method in terms of both accuracy of prediction and computation speed was the polynomial regression method. In this method, calculating with the 2nd order polynomial is both suitable for the physical model of the shots and the calculation is much faster.

Predictions were made using the same method, based on the 3D position information formed by the images obtained through the stereo vision system, providing the real physical environment.

Since it was predicted that the polynomial movement would occur from the 3rd frame. The estimation process continued from the 3rd frame till half of the total frames (by estimating the number of frames that can be obtained until ball bounce on table).

The prediction percentage success, which was around 84% in the 3rd frame, increased over 97% in the last prediction frame (middle frame). The difference between these percentages is entirely comes from image processing stage. Based on these data, it is predicted that the first data will be transmitted to the robot that will help the robot to gain time to take its first position for counter-attack.

Trajectory Prediction Method After Ball Bounces However, the prediction with the polynomial regression method will only be valid for estimating the position information of an object which has a polynomial motion. For this reason, it has been determined that different methods should be used to predict the secondary flight trajectory of the ball touching the table after bounce, the point at which the ball should be counterattacked and the type of counterattack.

For this reason, the trajectory prediction is divided into 3 stages. As we mentioned before first stage is the prediction of the point where it will touch the table (this phase has been successfully completed in this thesis). In order to predict the secondary trajectory of the ball (from the bouncing point to the hit point of the counterattack) and counterattack point, a simple and fast data filtering method can be used on ground truth data which has past shots recorded and quickly processed.

3.2.5. Robot Response

Robot response is based on the game type. There are lots of known striking types on table tennis. Some are specific for some game types. So it is important to know which type robot should be play and which type player want to play for training.

Reinforcement Learning Method For Best Response In addition, for the third prediction stage (the counterattack prediction), it is thought that by trying different stroke types for each trajectory (flight) data, with reinforcement learning method (reward-punishment values), calculating proximity between target point and the point where the ball returns (bounces back), system can learn how to return each ball. Preparing a robot (ball-throwing robot) which capable of shooting from different positions and with a trigger system that will allow the recording of exactly simultaneous images from the stereo vision system used for the physical environment, will reduce the learning time to minimum.

If enough shots can be made to create a ground truth data set with such a robot, (it has been calculated that there are approximately 150000 different shots in 3D plane with 50mm differences, and also all shots should be tested with different types of counter-attack), it will be possible to ensure that the system is a ready-to-play and learned system. If we do not have ground truth data yet, also system does responses randomly then learns to make it better after evaluating the results of strikes.

4. RESULTS AND DISCUSSION

To summarize this study and methods used, there are certain features that an artificial intelligence supported robotic system, which can be a table tennis training partner or trainer, must have. These features are: timing, robot, accessibility, learning.

- **Timing:** The system must be capable of finishing all predictions in a time of 50-60ms so that it can respond to attacking games.
- **Robot:** It must be a humanoid robot or robot arm that can respond to a fast game (it should be able to position in the relevant position in 50-60 ms and complete its movement for a counter strike). It is necessary to investigate whether there is a robot or robot arm with such high level reflexes. If not, this will be a separate research topic in the field of Mechatronics Engineering.
- **Accessibility:** If the system is to be converted into a product that can be used (accessible) by general users, it must be in a structure that can work with low-spec hardware as well.
- **Learning:** Since the machine learning parts can be realized through past shots, the system to be established should either be constantly watched different games and shooting types, or a ball shooter robot that can shoot different types of shots should be designed and the system should be learned with this robot.

5. CONCLUSION

Artificial intelligence supported systems are part of our lives for a while. AI-Supported systems are now used in military projects, automation systems, education, entertainment, sports competitions and even athlete training.

When it comes to artificial intelligence, the first thing that comes to mind is machine learning. Machine learning is simply an algorithm that enables an autonomous system to make a decision based on given inputs. Sometimes no inputs given but reward/punishment logic works on each step and find the best solution/prediction.

With machine learning, problems can sometimes be solved by analysis only on a data set. Also in variety of systems, the computer system can make predictions or make decisions by images obtained from the cameras with image processing methods. When it comes to the use of image processing methods, performance and hardware features become very important at this point. Because in computer vision based machine learning projects inputs/features comes from these hardware. Especially industrial cameras are used with high fps and/or low exposure time. Image processing methods used in computer vision problems are time consuming processes. So it would be better to do benchmarking for method selection.

Within the scope of this research project, a study was carried out on a computer supported stereo vision system for a real life problem. The main purpose of the study is to develop an artificial intelligence supported table tennis robot. Finding an appropriate partner or trainer for the players who plays table tennis is really a big difficulty. There are lots of studies about this subject. But all of them could reach the appropriate time usage for overall processes.

Every single hardware, method/algorithm and equipment selected for the best accuracy and less time usage. every single process should finish as quickly as possible. Because in an attack game on table tennis, ball flight time can be approximately 108ms.

If a final product would be produced with development of such a system, this product should be at prices accessible to those who want to use this system. Like in every subjects and every studies, the effort spent and the equipment used for this study should be in reasonable sizes. Therefore, the equipment used in this project has been tried to be kept at an achievable level for this sport branch.

If this study can eventually turn into a usable product, it will open a new page for the use of artificial intelligence in the field of sports.

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