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Robot-assisted Eye-Hand Coordination Training System by Estimating Motion Direction Using Smooth-Pursuit Eye Movements

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Abstract— **Robot-assisted eye-hand coordination rehabilitation training system is extremely urgent to study since recent evidence suggests that eye-hand coordination can be brutally disturbed by stroke with critical consequences on motor behavior. In this paper, we develop a robot-assisted eye-hand coordination training system by estimating motion direction using smooth-pursuit eye movements. Firstly, we design a Pong Game, which requires users to extrapolate the direction of a linearly moving ball and to predict whether this ball would be hit. Secondly, the motion direction of the ball is estimated via smooth-pursuit eye movements, allowing the robot quickly establish an assistive force field to hit the ball. Thirdly, adding haptic feedback technology into this training system to make users more immersive. Finally, we conduct a feasibility study with eight healthy subjects to verify the effectiveness of the proposed system. The experimental results show that the mean success rate for hitting the pong ball of the experiment group (assistance turn-on) is 28.33% higher than that of the control group (assistance turn-off), and the mean interception time of the experiment group is 0.35s shorter than that of the control group. Therefore, the developed system may be promising for transferring to the robot-assisted eye-hand coordination rehabilitation training for post-stroke patients.**

I. INTRODUCTION

Stroke is the leading cause of disability in the world, upper limb motor impairment is a sequela in 80% of patients. Specifically, eye-hand coordination constitutes a critical factor that is conditioning the upper limb rehabilitation progress [1]. In particular, the eye-hand coordination is the ability of the central nervous system to coordinate the information received through the eyes to control, guide, and direct the arm/hand in the accomplishment of a given task [2]. As the dynamics between visual guidance and manual motor control are disturbed, patients may experience subclinical impairments, amplifying functional loss [3]–[5]. Hence, the robot-assisted eye-hand coordination training system is extremely urgent to study for improving users' motor ability.

Up to now, only a few rehabilitation robots have explored the gaze-tracking guidance mode for upper limb robot-assisted neurorehabilitation. In particular, the robot assistance is activated by the detection of the intention of movement of the patient with his/her gaze. Since the eyes are known as a window into the human mind; they can provide information about our intentions, emotional and mental states, as well as where our attention is focused [6]. For instance, Javier et.al used a multi-layer perception to identify the toys (target) that the user wants to reach, according to the user's gaze and the robot's position/velocity [7], [8]. Similarly, Vincent et.al proposed the fixation score approach to best detect the user's intention in reaching actions when assisted by a robot [9]. Actually, these studies employed a task which is similar to the pick-place task, which requires users to gaze at a motionless object, then the robot quickly turns on movement assistance to reach the selected target predicted via the user's gaze information [10]–[14]. Consequently, these approaches focus on providing more natural interaction by involving gaze information, which may not help train or recover the eye-hand coordination ability. Since there is evidence to suggest that pursuing the moving object increases the user's dynamic visual acuity and therefore enables the user's eye-hand coordination ability [15].

Such being the case, the task of pursuing moving objects (such as ball sports) needs to be exploited. This task requires users to keep their eyes smooth pursuit the moving ball to hit or catch it reliably, and its success often depends on the ability to predict the direction of moving objects [15]–[19]. Hence, the key for robot-assisted hitting/catching the moving objects is how to estimate its motion direction according to smooth-pursuit eye movements [20]. Next, the robot-assisted force field needs to be established according to the estimated motion direction for aiding users to hit or catch the ball.

Consequently, this paper develops a robot-assisted eye-hand coordination (RA-EHC) training system, which aims to provide a motion direction estimation via smooth-pursuit eye movements, then allowing the robot quickly turn on assistance to accomplish the task, as shown in Figure 1. The rest of this paper is organized as follows: Section II describes the RA-EHC system. Section III shows the experiment setup and results. Finally, conclusion & future work is presented in Section IV.

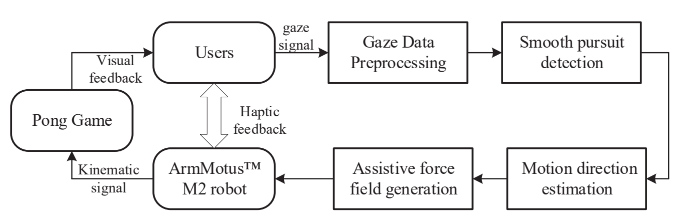

Fig. 1. The basic flowchart of the RA-EHC system based on eye movement.

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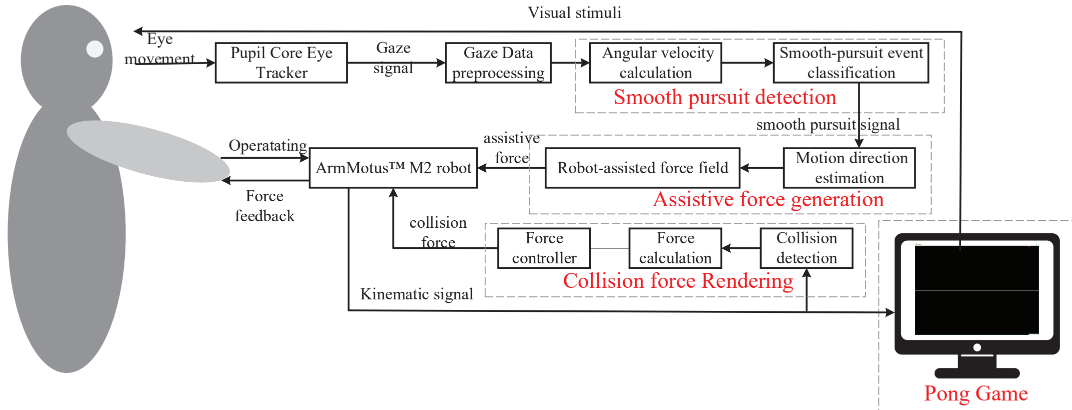

Fig. 2. The system structure of RA-EHC system, detailed explanation in Section II-A.

II. RA-EHC System

A. System Structure

The detailed system structure was shown in Figure 2. This system was composed of Pupil Core Eye Tracker, $\mathrm{ArmMotus}^{\mathrm{TM}}$ M2 robot and computer device. The Pupil Core Eye Tracker would track and collect the user's eye movements in real-time. $\mathrm{ArmMotus}^{\mathrm{TM}}$ M2 robot was used to assist the upper limb of the user, each sensor embedded in the robot collected kinematic signals of the end-effector in real-time. The computer was connected to the Pupil Core Eye Tracker and the $\mathrm{ArmMotus}^{\mathrm{TM}}$ M2 robot, respectively, which ran a Pong Game. The eye movement captured by the eye tracker was originally based on the World Coordinate, then convert to the Screen Coordinate by using the official AprilTags tag pictures for positioning. Furthermore, Screen Coordinate, Game Scene Coordinate, and ArmMotus™ M2 Robot Coordinate could transform each other according to coordinate transformation. The basic flowchart of this system is as follows: firstly, the eye movement is recorded and preprocessed. Secondly, its smooth-pursuit part is detected by using event classification. Thirdly, the motion direction of the moving ball is estimated based on the smooth-pursuit eye movement by using linear regression. Finally, this system allows the robot to quickly establish the assistive force field for hitting the ball according to motion direction estimation. Besides, to enhance the interactive experience, the collision force rendering was added except for the assistive force generation. The collision force rendering module mainly includes collision detection, force calculation, and force controller. Overall, there were both visual feedback and haptic feedback to enhance users' engagement and motivation in this system.

B. Pong Game

Pong Game is a popular game worldwide that requires fast and powerful shots, which is extensively involved in eye-hand coordination. Hence, the game scene of the RA-EHC system was designed as Pong Game. As shown in Figure 3, this game scene consists of a red pong ball, a white racket, and a white tennis net in the middle under the black background. The end-effector of the ArmMotus™ M2 robot corresponds to the white racket in the scene. In particular, the diameter of the red pong ball is 10 pixels, and the length of the white racket is 100 pixels. In order to increase the difficulty to this game, the red pong ball will be invisible after moving for 0.7 seconds, the invisible area was as shown in Figure 3. During each training trial, users place their forearms on the cuff and hold the handle. Once the Pong Game is launched, the red ball is designed to move in a straight line, users smooth pursuit the moving ball and operate the end-effector of the robot to hit it. Once the ball is successfully hit, the racket stops and the next trial will start. If failing to hit the ball, after the ball pops off the edge of game scene the next trial will start.

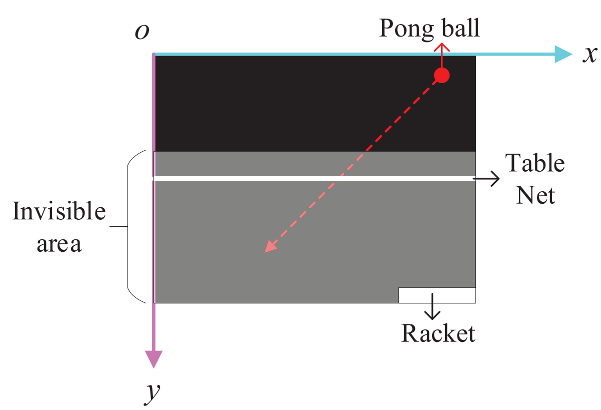

Fig. 3. There are a red pong ball, a white racket, and the table net in Pong Game Scene, the gray area is invisible to the red pong ball.

C. Gaze Data Preprocessing

The Pupil Core Eye Tracker with the sampling frequency of 200 Hz, the gazing accuracy of 0.60°, and the gazing precision of 0.02° was used in this paper. The Pupil Capture software records users' gaze signals in real-time. The eye tracker needs to be calibrated before using it, firstly, the eye tracker is stably worn on the user's head and connected to the computer through a USB cable. Secondly, click the calibration button of the Pupil Capture software to start the calibration procedure. Thirdly, the user needs to gaze at five black circular calibration points on the screen in turn to complete the calibration procedure.

In general, the "confidence" parameter λ represents the reliability of the original gaze signal, it ranges from 0 to 1, and the larger it is, the more reliable the gaze signal [21]. In particular, if $\lambda \leq 0.6$, the eye movement data is abandoned. Next, Kalman Filter was used to filter the eye movement to further improve the quality of the signal.

D. Smooth Pursuit Detection

In general, the user's eye movement may be a fixation, smooth pursuit, and saccade mixed while pursuing the moving object [22]. So detecting smooth-pursuit eye movements is necessary for motion direction estimation. In order to ensure the real-time performance of the system, velocity and velocity threshold identification (I-VVT) was adopted to detect the smooth-pursuit eye movements [23]. Hence, calculating the angular velocity of eye movement is necessary. The method for calculating angular velocity of eye movement was shown in Figure 4, assuming that the eye moves from point A to point B, and their coordinates are (x_{i-1}, y_{i-1}) and (x_i, y_i), respectively. The vertical distance from the user's eye to the screen is l, then the angular velocity w is:

$$w = \frac{180}{T\pi} \cdot 2 \cdot \arctan\left(\frac{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{2l}\right) \tag{1}$$

where T is the sampling period of the eye tracker.

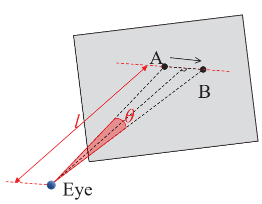

Fig. 4. The angular velocity calculation.

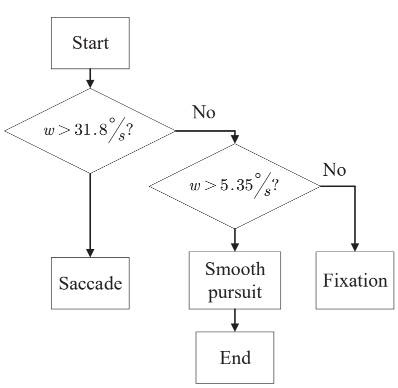

Fig. 5. The event classification for smooth pursuit detection by I-VVT.

Furthermore, Figure 5 shows the diagram of event classification by I-VVT: (1) if $w > 31.8^o/s$, then the eye movement belongs to saccade; (2) if $5.35^o/s \leq w < 31.8^o/s$, then the eye movement belongs to smooth pursuit; (3) if $w < 5.35^o/s$, then the eye movement belongs to fixation [24].

E. Assistive Force Generation

1) Motion Direction Estimation: Specifically, we designed a task, "Pong Game", which required users to extrapolate the direction of a linearly moving pong ball and to predict whether the racket would hit or miss the ball. Therefore, the motion direction estimation of the moving pong ball is necessary. Firstly, the detected smooth-pursuit eye movements were fitted by the linear regression. Secondly, according to this fitted line, the motion direction, that is, the angle α (as shown in Figure 6) between the estimated trajectory and y-axis is calculated. Finally, the assistive force field was generated according to this estimated motion direction α.

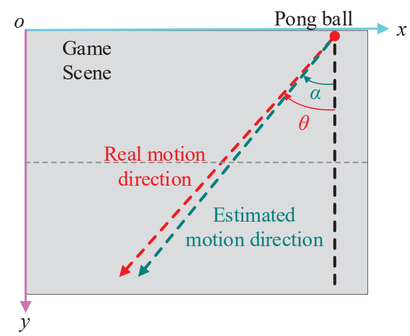

Fig. 6. The motion direction estimation by using linear regression, the red dotted line is the real motion of the pong ball, and the blue dotted line is the estimated trajectory of the pong ball. α is the angle between the estimated motion and the y-axis, and θ is the angle between the real motion and the y-axis.

2) Robot-assisted Force Field: For some users with dysfunction in the eye-hand coordinate ability, they may not successfully hit the ball. In this paper, the robot-assisted force field was generated to help users hit the ball. It was perpendicular to the estimated motion trajectory, which allowed the fastest hitting and the shortest reaction time for training users' eye-hand coordination ability. There were two conditions for starting this force field, one is receiving the force when users grip the robot's end-effector; the other is completing the motion estimation by smooth-pursuit eye movements. As shown in Figure 7(a), the assistive force was as follows:

$$F_{assist} = \begin{cases} F_m & d \geq d_m \\ k(d - d_0) & d_0 < d < d_m \\ 0 & d \leq d_0 \end{cases} \tag{2}$$

where, $F_m = 30$N is the maximum assistive force, $d_m = 300$ pixel is the critical distance from the straight line, they were determined by a preliminary experiment for providing an appropriate force field, for example, if F_m is too large, the start acceleration is too large, which is easy to cause injury to users. $k = 0.15$ is the gain factor of assistive force, d is

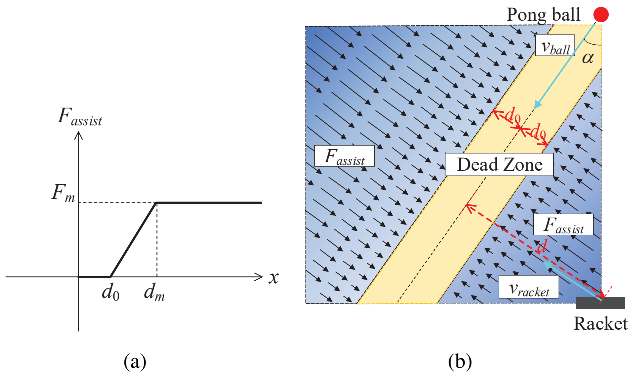

Fig. 7. The assistive force generation according to the estimated motion direction. (a) the assistive force model. (b) the robot-assisted force field.

the distance from the straight line, and $d_0 = 100$ pixel is the dead band of force field.

In particular, the force field has two part: assistive force field $(d \geq d_0)$ and dead zone $(d < d_0)$, as shown in Figure 7(b). In the assistive force field, the farther away the racket is from the free field, the greater the force is. When d exceeds the critical distance d_m, the force will not increase and maintain at the maximum force F_m. In the dead zone, the user is free to control the racket to hit the ball without any assistance, which could increase users' engagement to get better training performance than always assistance.

F. Collision Force Rendering

In order to enhance the immersive experience for users, the collision force rendering contains three modules: collision detection, force calculation, and force controller. Firstly, we detected the collision between the racket and the ball by using *pygame* development library. Secondly, assuming that the collision process obeys the conservation of momentum and conservation of energy. Furthermore, the surface of the ball and racket is smooth and the collision between them is completely elastic, only the force which is perpendicular to the racket is considered, as shown in Figure 8. Detailed force calculation was as follows:

$$m_b v_{b0} + m_p v_{p0} = m_b v_b + m_p v_p \tag{3}$$

$$\frac{1}{2} m_b v_{b0}^2 + \frac{1}{2} m_p v_{p0}^2 = \frac{1}{2} m_b v_b^2 + \frac{1}{2} m_p v_p^2 \tag{4}$$

where, m_b is the mass of the pong ball, m_p is the mass of the racket, v_{b0} is the velocity of the pong ball before the collision, v_{p0} is the velocity of the racket before the collision, v_b is the velocity of the pong ball after the collision, and v_p is the velocity of the racket after the collision.

According to the above equations, v_b represents as follows:

$$v_b = \frac{(m_b - m_p) v_{b0} + 2 m_p v_{p0}}{m_b + m_p} \tag{5}$$

According to Newton's Second Law of Motion, the collision force $F_{collision}$ is:

$$F_{collision} = m_b a_b = m_b \frac{\Delta v_b}{\Delta t} = m_b \frac{v_b - v_{b0}}{\Delta t} \tag{6}$$

where, a_b is the acceleration of the pong ball, Δt is the duration of collision between the pong ball and racket. In general, $\Delta t = 5$ ms, $m_b = 0.1$ kg

Finally, the collision force was rendered by calling the SDK of $\mathrm{ArmMotus}^{\mathrm{TM}}$ M2 robot.

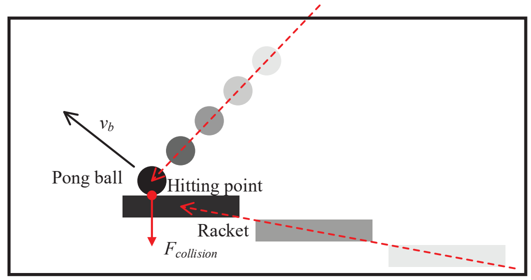

Fig. 8. The collision between the racket and the pong ball.

III. Experiment & Results

To verify the effectiveness of the RA-EHC system, the experiment for accuracy evaluation of motion direction estimation and the experiment for feasibility verification of RA-EHC system were carried out.

A. The Experiment for Accuracy Evaluation of Motion Direction Estimation

1) Experimental setup: As shown in Figure 9, in order to avoid the posture changing of the user's head, the user's chin was placed on the supporting rest. In each trial, users were asked to wear an eye tracker in their head and stared at the red pong ball in the Game Scene, and they wouldn't have to operate the ArmMotus™ M2 robot. After the game is launched, the pong ball will move along a straight line, users' eyes need to quickly track the movement of the pong ball. Then the eye movement signals were collected and the

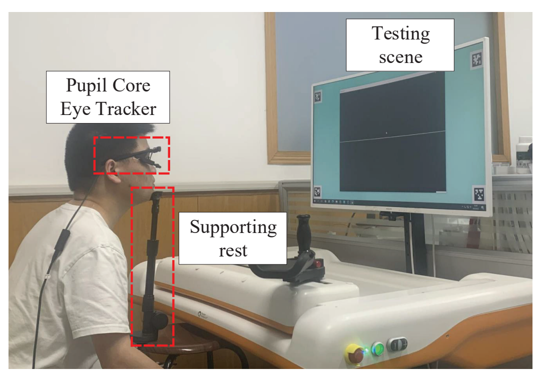

Fig. 9. The experiment scene for accuracy evaluation.

smooth-pursuit part was detected and regressed by linear regression. The angle error between the regressed motion and the real motion was used to evaluate the accuracy of motion direction estimation, as shown in Figure 6. The angle error $angle_e$ is defined as:

$$angle_e = \alpha - \theta \tag{7}$$

where, α is the angle between the estimated motion and the y-axis, θ is the angle between the real motion and the y-axis. Obviously, the smaller the angle error is, the higher the accuracy of the motion direction estimation is.

2) Results: In this paper, the down-sampling for real-time motion direction estimation was adopted to meet the requirements of both accuracy and time. In practice, the first 30 points in each trial were involved, and each group of 5 points was averaged, and then liner regression was performed. An example of motion direction estimation of

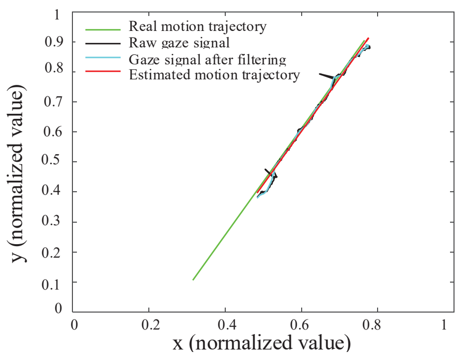

Fig. 10. The results of motion direction estimation for one trial based on smooth-pursuit eye movements.

one trial was shown in Figure 10, the green line was the real motion trajectory of the pong ball, the black line was the raw eye movement, the blue line was the eye movement after filtering, and the red line was the estimated motion trajectory. Obviously, the green line was very close to the estimated red line, which indicated that the motion direction of the pong ball can be better estimated by linear regression. Besides, the angle error of 30 trials carried in this experiment ranged from $-1.86^o \sim 1.14^o$, and the smallest angle error was -0.09^o, which was in the allowed range.

B. The Experiment for Feasibility Verification of RA-EHC System

1) Experimental setup: The experiment for feasibility verification of the RA-EHC system contains two groups: the control group and the experiment group. In the control group, as shown in Figure 11(a), users were asked to track the red pong ball in the Game Scene and operate the robot to hit the ball without assistance once the game was launched. In the

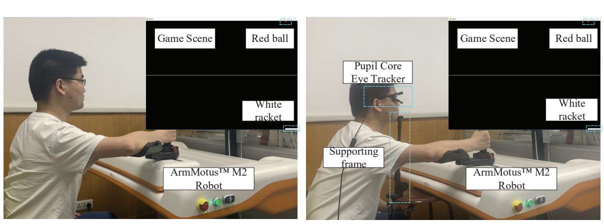

Fig. 11. The experiment scene for feasibility verification of the RA-EHC system. (a) the experiment scene of the control group. (b) the experiment scene of the experiment group.

experiment group, as shown in Figure 11(b), everything is the same as that of the control group except hitting the ball with assistance. 8 subjects (2 females and 6 males, aged 24$\sim$27 years old, numbered S1$\sim$S8) were recruited to participate in this experiment. Each subject was required to conduct both control group training and experiment group training, and each training group contained 30 trials, and each subject was evaluated independently after training. In particular, there were two indicators to evaluate the feasibility verification of the RA-EHC system: success rate (%) and intercept time (s). The success rate is the number of trials where the pong ball is successfully hit divided by the total number of trials. The intercept time quantified the amount of time used for hitting the ball after the racket started up.

2) Results: As shown in Table I, the mean success rate of the experiment group was 28.33% larger than the control group. Take S6 as an example, the success rate of the experiment group was 93.33% and the success rate of the control group was 60%, the improvement was 33.33%. According to the T-test results, there were significant differences ($p = 8.1874e{-}06$) between the control group and experiment group in terms of success rate, which indicated that the developed system turned on the assistive force could aid users to accomplish the Pong Game more successfully than that of the system turned off the assistive force. Furthermore,

TABLE I

THE SUCCESS RATE OF ALL SUBJECTS IN THE CONTROL GROUP OR THE EXPERIMENT GROUP.

Users (CG)	success rate	Users (EG)	success rate
S1	73.33%	S1	96.67%
S2	56.67%	S2	83.33%
S3	46.67%	S3	76.67%
S4	63.33%	S4	83.33%
S5	63.33%	S5	96.67%
S6	60.00%	S6	93.33%
S7	50.00%	S7	76.67%
S8	56.67%	S8	90.00%
Mean	58.75%	Mean	87.08%

CG = Control Group, EG = Experiment Group.

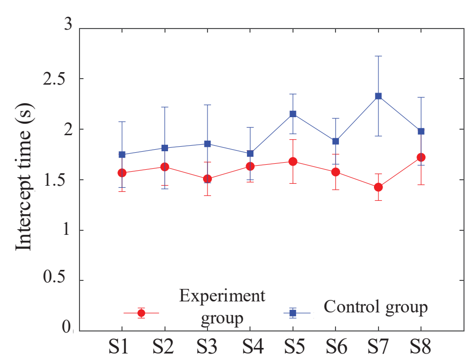

Fig. 12. The intercept time of the control group and the experiment group.

as shown in Figure 12, the mean intercept time of the experiment group was 0.35s shorter than the control group. These indicated that users can manipulate the racket faster and accurately hit the pong ball under a robot-assisted force

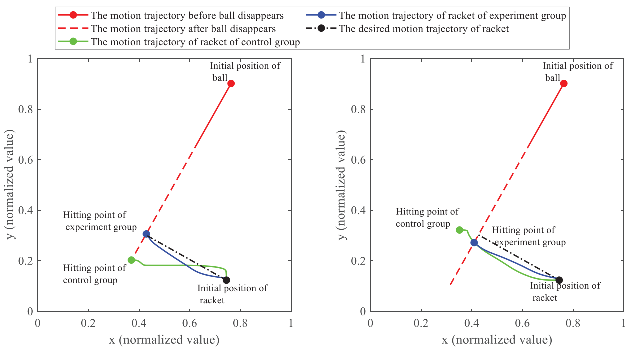

Fig. 13. The trajectories of the pong ball and racket while playing the Pong Game.

field. Besides, the trajectory of the pong ball and racket with and without assistance were as shown in Figure 13. In the case of assistance, the trajectory of the racket was shorter and smoother than that of the case without assistance and was closer to the ideal trajectory.

IV. Conclusion & Future Work

This paper develops a novel RA-EHC training system with haptic feedback technology by estimating motion direction using smooth-pursuit eye movements. According to experimental results based on two assessment metrics (the success rate and intercept time), the performance of the experiment group is better than that of the control group, that is, the developed system has the potential for training patients' eye-hand coordination ability. In the future, we will conduct the experiment with post-stroke patients to verify the training effectiveness of the RA-EHC system.

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