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Real-time posture feedback for effective motor learning in table tennis in virtual reality☆

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A B S T R A C T

Table tennis is a demanding sport in terms of motor skills, requiring precise time-critical postures and techniques for the player to excel. Therefore, it is a compelling case study for motor learning in Virtual Reality (VR). Though VR table tennis training applications have been used to study the learning process in VR, each has not fully explored the role of real-time feedback on motor learning, which is a fundamental component of real-life table tennis training. To address this, we have developed a training system that provides multi-modal training instructions and real-time posture guidance feedback to assist beginner players in improving their playing outcomes. This system synthesizes a table tennis training environment by providing realistic visual and audio stimuli that includes a custom highly-accurate physics implementation of ball flight. An experimental group ($n = 9$) trained to learn correct posture and paddle handling for forehand and backhand drives. The results show that the participants improved significantly in terms of technique and ball return quality. This work is the first VR table tennis system that provides real-time posture feedback using a low-cost depth camera. Additionally, the participants' significant improvement in playing posture over a short period of time shows the integral role of feedback in learning and further validates VR as an effective motor learning tool.

1. Introduction

VR's ability to create rich and compelling experiences drives research in a variety of domains beyond entertainment. One such area of interest is the use of VR for training purposes. In particular, VR is well-suited to teach coordinated motor tasks, which is especially important in many sports. If a person intends to learn a new sport, physically performing the activity and performing it correctly will pave the way for better long term outcomes. Intuitively, a person who only gains theoretical knowledge of a sport through reading and watching videos will generally be no match for players that have had professional instruction and numerous hours of practice. Developing the ability to play a new sport and retain that ability requires the repetitive coordination of the brain and muscles (Goodway et al., 2019). Out of all computerized training methods, VR is particularly suited to aid in developing these motor skills because it creates the sense of being "present" in the environment (Sanchez-Vives and Slater, 2005; Vignais et al., 2015).

The power of VR for sports training is that it targets a player's visual, auditory, and kinaesthetic learning styles by simulating sports activities from a first-person stereoscopic perspective, creating a sense of presence while helping the player to develop the perceptual and motor skills needed for the real sport (Allcoat and von Mühlenen, 2018; Bideau et al., 2003; 2009; Vignais et al., 2015). In some cases, VR can make up for the absence of real equipment, an appropriate training environment, a knowledgeable trainer, or other players, and can additionally provide benefits over real training. VR can be used to dynamically tailor training sessions to the player's unique needs, create controlled scenarios that are not possible in the real sport, and provide feedback during or after the training session. How well a motor task can be learned in VR is still an open question, complicated by hardware concerns such as the weight, field of view and refresh rate of the headset, and the fidelity of the visual, audio, and haptic experience. Yet it is evident that motor learning is possible in VR, as demonstrated by participants' successful acquisition of motor skills in other VR sports studies (Checa and Bustillo, 2020; Miles et al., 2012).

Though a variety of sports have been the subject of VR training research, one sport in particular that lends itself well to virtualization and academic study in VR training is table tennis, as evidenced by the

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many VR training studies with table tennis as their central focus (Brunnett et al., 2006; Knoerlein et al., 2007; Li et al., 2010; Miles et al., 2012; Raab et al., 2005; Todorov et al., 1997). From a practical implementation standpoint, table tennis is a sport involving minimal haptic interactions where each player remains relatively in-place, making it a good fit for the spatial and haptic limitations of VR. The sport is visually demanding, requires optimal posture and precise time-critical movements, necessitates fast decision-making skills and involves an innate understanding of the mechanics of ball flight (Wong et al., 2020). Combined, these qualities make table tennis an ideal testbed to investigate the learning of motor skills using VR, and it has indeed been used before in the study of VR motor learning (Raab et al., 2005; Todorov et al., 1997).

A common limitation of the existing work is the lack of either informative or guidance feedback (Brunnett et al., 2006; Eleven: Table tennis vr, 2021; Li et al., 2010; Michalski et al., 2019), even though both feedback types are of high importance for motor learning (Salmoni et al., 1984). In other sports, motion capturing technology has been used for feedback and performance analysis (Bideau et al., 2009; Covaci et al., 2015; Göbel et al., 2010); however, it hasn't been utilized for real-time posture training in table tennis. In existing table tennis simulations, the measurement of success is based on output, such as whether the ball successfully lands on the opposite side of the table and the speed of the ball. This standard of assessment fails to consider that posture and technique are key to improving these outcomes. While it is entirely possible to produce decent outputs with improper posture and techniques, an incorrect form may hamper the player's ability to improve. Additionally, incorrectly practicing a technique may make that playing style a habit that is difficult to correct later (Goodway et al., 2019). Posture training may not produce an immediate outcome of an increased number of balls on the other side of the net, but it is an integral component of learning fundamental motor skills that could promote more effective long-term outcomes. Professional trainers focus more on solidifying foundations that could be beneficial for broader skill sets (Barczyk-Pawelec et al., 2012; Raab et al., 2005; Wong et al., 2020). It is vital that table tennis be taught with an emphasis on posture and technique instead of simply having the player attempt to get the ball over the net. Even though it is intuitive that correct posture has a crucial role in table tennis training, there has been no VR study that focuses on the impact of real-time posture training and feedback for motor skill training. Consequently, no VR table tennis system exists that offers real-time posture training feedback.

To demonstrate the power of real-time posture feedback for fine-grained motor learning, we have developed a VR system that trains beginner players to perform basic table tennis maneuvers using a low-cost depth camera. The system provides a high-fidelity ball flight physics simulation and a real-time instruction-based training feedback scheme to replicate the real table tennis training environment conditions. Replicating the real training environment is intended to improve ecological validity, creating similar training conditions that lead to better motor skills. To achieve this goal, we partnered with a professional player with over 25 years of experience who has won the Colorado State Table Tennis Championship and runs a training center. We utilized a Vicon motion capture system to accurately and smoothly record his playing posture, which we used for the VR training system. We are going to refer to him as "the trainer" throughout this manuscript. The captured playing movements were then converted to an animated avatar in the Virtual Environment (VE) and used to teach correct playing postures. The posture training scheme offers the basic returning techniques of forehand and backhand drives, and increases trainees' awareness of incorrect posture by presenting indicators and guiding them to perform the correct movements. The player (user) is presented with training instructions in the VE in multiple modalities, and the player's pose is recorded using a Microsoft Kinect 2. The player's posture at each time step is compared to the avatar's posture. The similarities between the joint angles of both models are assessed and presented to the player to adjust their technique as needed. Additionally, the paddle pose and ball trajectory are also recorded to assess paddle handling techniques.

We hypothesize that VR table tennis training with real-time posture feedback will produce postures and techniques that will be more aligned with the recorded movements of the trainer. If our system replicates the real-life training conditions accurately, the training system will teach motor skills effectively. This hypothesis is based on existing literature regarding learning and training in both real and VR, where training has shown improvement in skills in post-training analyses (How to play table tennis, 2017; Raab et al., 2005; Wong et al., 2020). For this study, we decided on five training sessions as the time frame of the experiment. This decision was based on consultation with the trainer and data from his center. The center's data show that we can see the modification of motor skills towards that of a professional player after five sessions. Our study examines how well participants can learn forehand and backhand drive returning techniques and improve their playing posture, which is detailed in the following two secondary hypotheses:

- H1: The player's joint angles will improve significantly toward the joint angles of the gold standard movement model after five training sessions in VR.
- H2: The player's paddle control and ball returning angles will improve significantly after five training sessions in VR.

Modifications in posture and returning technique, if improved, lead to improvements in ball return trajectories and speed. Therefore, the focus of this study is on posture, technique, and the returned balls' trajectory and speed rather than the number of returned balls. Increasing the number of returned balls is more of a natural long-term outcome as they gain proper motor skills, not an immediate goal of this study. For this reason, we do not necessarily expect the number of returned balls to increase.

We recruited nine individuals with no experience in table tennis for this study. Participants were trained in forehand and backhand drive return techniques using the VR table tennis system for five sessions (45 minutes each). We compared skeleton joint angles and paddle controlling data between the pre-training and post-training sessions. The results showed significant improvement in both posture and paddle handling techniques, which led to a significant ball trajectory improvement in terms of lower and faster ball returns. Both parametric paired-samples *t*-test and non-parametric Wilcoxon signed-rank test were used for statistical analysis. This study's results validate our system's effectiveness in teaching and reinforcing certain skills necessary for table tennis in VR and show that real-time posture feedback activates motor learning. Additionally, we want to emphasize that the motor skills and ball returning techniques training in this study only apply to the virtual environment. The skill transfer from VR to real-world table tennis performance and VR training's effectiveness compared to real training are out of this study's scope. However, both goals are part of future work.

The contributions of this study are twofold. On the technical side, our system offers a VR table tennis system that emphasizes correct posture and technique using real-time feedback that is a low-cost and beginner-friendly training platform. To our knowledge, no such system exists for table tennis training. On the fundamental side, this study demonstrates the motor learning process occurring in VR for a skill-based sport when the training is based on real-time posture feedback. This study opens the door for a more in-depth investigation into the motor learning process in VR, how we might accelerate the learning, and how we could apply it to other domains outside of sports. It also adds to the existing literature that supports the validity of VR for learning and training, specifically in table tennis.

2. Related work

The question of how VR can be used to enhance and augment the motor learning process, as well as the efficacy of such training, has been investigated for a variety of sports such as dart throwing (Tirp et al., 2015), juggling (Lammfromm and Gopher, 2011) rowing (Rauter et al., 2013), archery (Göbel et al., 2010), baseball batting (Gray, 2017), tennis (Xu et al., 2009), and American football (Huang et al., 2015). VR has certain detriments, including limited ability to move about an environment and lack of tactile fidelity. Yet, VR possesses particular strengths as well, among which are the ability to “overtrain” an individual by making the task more difficult than in real life, the ability to customize scenarios to a player’s particular needs, and the ability to reproduce specific scenarios any number of times (Miles et al., 2012).

Studies have been conducted to determine the key variables necessary for successful sports training for virtual environments and the real world. The fidelity of a virtual sport has been found to play a significant role in how effectively we can learn that sport in VR and how well the learned skills transfer to the real world. A study by Miles et al. states that the realism of the activity, and particularly the accuracy of the physics implementation for ball sports, needs to be high for the virtual environment to be effective (Miles et al., 2012). Studies have also determined that variety plays a significant role in successful skill acquisition, and have highlighted the importance of both technical and tactical training, not just in isolation but also in combination (Checa and Bustillo, 2020; Miles et al., 2012; Raab et al., 2005). Feedback to the user, both in the form of informative feedback and guidance feedback, is a crucial part of training (Salmoni et al., 1984). The use of motion capture technologies for this purpose, as well as performance analysis, has been explored in multiple studies (Bideau et al., 2009; Covaci et al., 2015; Göbel et al., 2010).

A study by Michalski et al. specifically investigated training transfer from VR table tennis to real-life table tennis and found significant improvement as a result of VR training (Michalski et al., 2019). This study is one of the most recent table tennis training systems in VR with a similar virtual environment to ours. However, the study measures success based on the number of the returned balls and doesn’t train the subjects to perform correct posture and return techniques as our system does. Another noteworthy study by Todorov et al. found good transfer from VR table tennis training to the real-life sport, and additionally investigated the fundamental aspects of the VR training environment that contribute to improved outcomes, finding that providing feedback to the players while training enhanced the learning process (Todorov et al., 1997).

3. System design

The VR Table Tennis (VRTT) system, shown in Fig. 1, is a VE developed with Unity Engine that offers realistic table tennis training through multi-modal instruction and continuous feedback on posture and technique. The player uses an HTC Vive headset and an HTC Vive racket with an HTC Vive tracker attached to it. The overall system (shown in Fig. 2(a)) consists of three main components. First, the physics simulation of ball flight and collision behaviors. Second, pre-recorded motion capture data of a professional player (the trainer) as a training model and gold standard measurement. Third, a depth camera capturing the trainee’s skeletal information in real-time for posture and technique analysis to provide feedback. The system trains participants to perform forehand and backhand drive ball return maneuvers correctly. Briefly, VRTT combines an accurate ball physics simulation and a real-time feedback system to provide a complete training platform.

3.1. Physics simulation and validation

We have developed our own ball flight physics simulation due to the limitations of the generic physics simulations (PhysX) provided by Unity. Table tennis is a fast game that requires accurate collisions and simulations of spin-related phenomena such as the Magnus effect, neither of which are provided in Unity. Therefore, we have developed our own physics simulations that overcome these limitations. The simulated physics provides accurate ball flight and rebounding off of the paddle and table. The ball loses energy during collisions, and spin is imparted to the ball from friction with collided surfaces. Air drag, gravity, and Magnus effect behave based on a realistic physics model.

To validate our physics simulations, we designed an experiment to compare our model with real ball flight and collision behaviors. Fig. 3(a) shows the experimental design, which consists of a dotted sheet behind the table, a Huipang HP-07 ball launcher situated at the edge of the table closest to the sheet, and two cameras at two different locations, each running at 240FPS with 1080p resolution. To accurately measure ball speed, the camera located on the table records the ball as it moves in front of the dotted sheet, which is used as a physical reference with a known distance between points (2.74 cm). Similarly, the ball trajectory is tracked using the far camera’s view of the ball and dotted sheet.

Balls with speeds varying from 4.39 m/s (speed A) to 6.46 m/s (speed B) were shot from the launcher and recorded by both cameras. For each case with a particular speed, the same scenario was repeated in the VE to

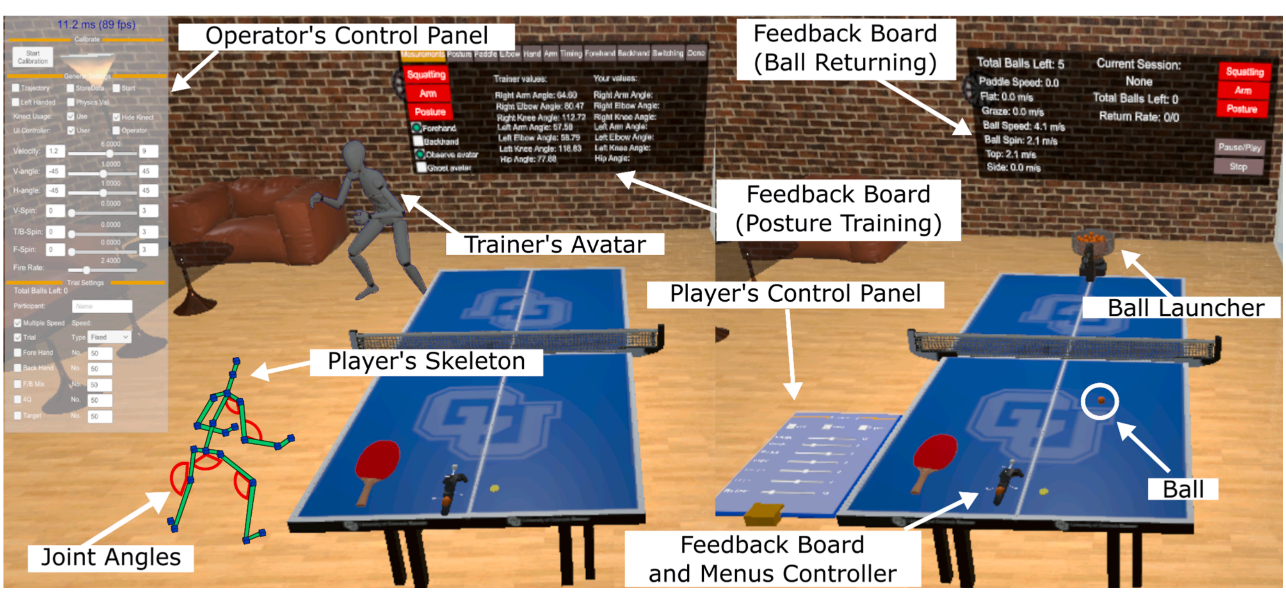

Fig. 1. The virtual environment of the table tennis system is designed to resemble a real table tennis play area.

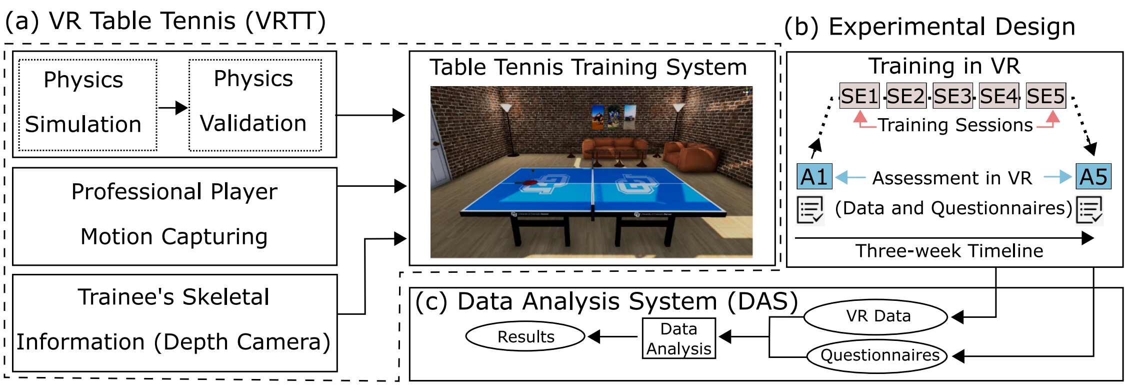

Fig. 2. Overall methodology, consisting of the system design and experimental design, then generating data to evaluate the study.

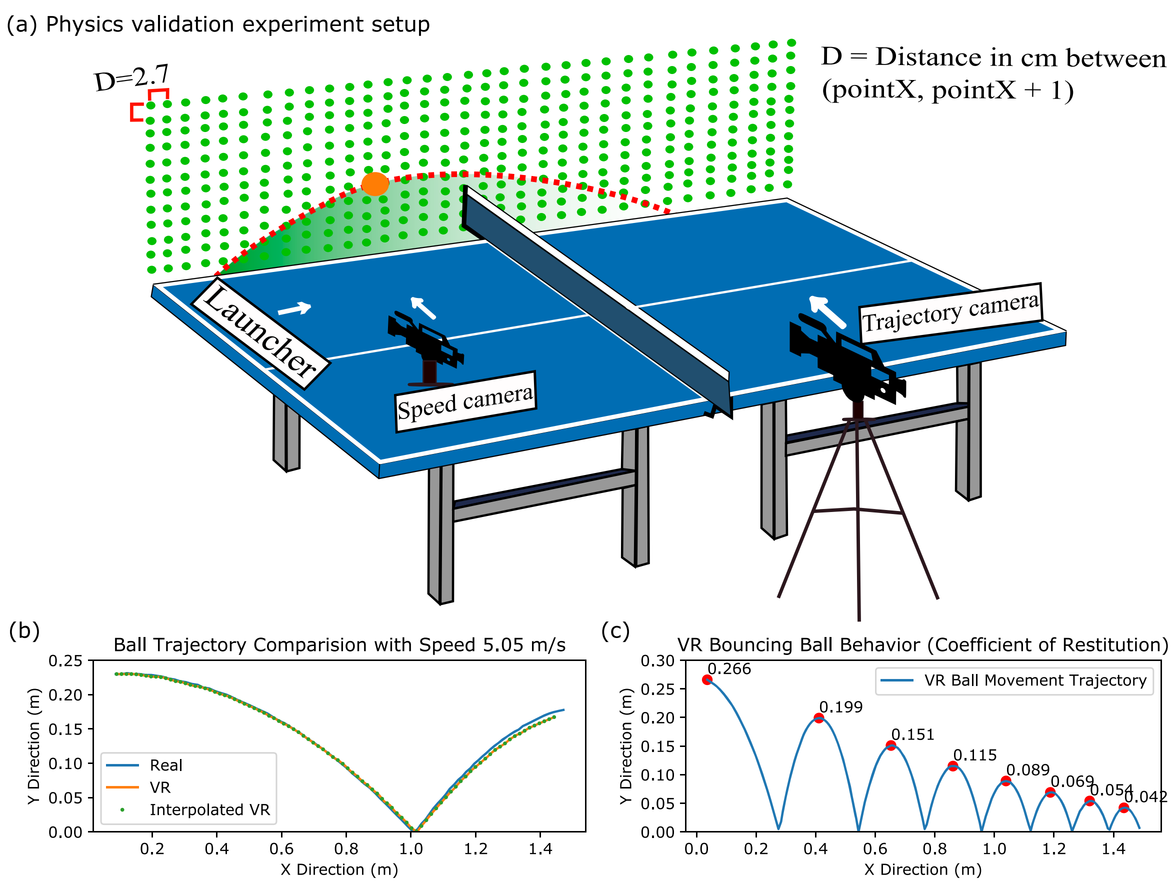

Fig. 3. Physics validation experiment setup and its results. The results show the realistic ball flight trajectory and collision behavior.

compare both the real and VR balls' trajectory and collision behavior to show the simulation's accuracy. We did not validate ball spin explicitly in this experiment; therefore, we reduced the spin to the minimum in the real launcher. The speed and spin are coupled in the launching machine; when both top-spin and side-spin are equal, the ball trajectory shows little to no deviation due to spin. If our launcher had accurate spin configurations, we could validate the spin as well. Nevertheless, we implemented the spin with known mathematical models, which provide crucial effects such as the Magnus effect that contributes to the ball trajectory.

Fig. 3 (b) shows the similarity between the real ball trajectory and the ball generated in VR for the same speed. As shown, the trajectories of both are only shifted by a small amount after the rebound off of the table. To quantitatively compare the two trajectories, we used the Dynamic Time Warping (DTW) approach. The Euclidean distances between the VR and real trajectories for all the balls with speed A and speed B are between 2m to 2.5m with normalized scores of between 0.01255 to 0.00734, which means they are very similar (an exact trajectory will have a score of 0)(Berndt and Clifford, 1994).

To analyze the ball rebound's physics, we conducted another experiment in the VE to test the coefficient of restitution, which represents how much the ball must rebound when it collides with a surface such as a table. According to the International Table Tennis Federation (ITTF), when the ball is dropped from a height of 30 cm it should bounce up about 23 cm (approximately 76.6%) (Handbook - international table tennis federation, 2020). Fig. 3(c) shows the results of our experiment where we dropped the ball and let it hit the table seven times to show that the ball precisely loses the energy at each collision. Our results show a 76.68% bounce on average for each dropping case which is an accuracy of 99.76%. The results show that the simulated physics provides a realistic replication of table tennis ball flight. Additionally, the professional trainer tested the system to examine its validity from a professional player perspective. He reported very positive feedback regarding the realistic behavior of the physics simulation.

3.2. Training system and feedback loop

The VRTT training system consists of two main parts: posture training and paddle controlling (ball returning) training. In this study, the participants are trained to learn two of the most basic table tennis strokes: the forehand drive and the backhand drive. Detailed instructions were given as part of the training on correctly performing the maneuvers via animated images, static images, and text. The instructions and controlling menu were shown on a feedback board placed in front of the trainee in the VE as shown in Fig. 1. The instructions for both forehand and backhand drives described below were a combination of instructions provided by the trainer and information from other professional table tennis experts (How to play table tennis, 2017). The instructions include the right way of poses and guidelines on paddle controlling techniques as well.

- Forehand Drive The feet should be wider than shoulder-width apart, with the dominant foot placed about a half-step back from the non-dominant foot. The body should be crouched and forward with knees bent and arms in front of the player. Once the ball is launched, the player should start a backswing motion, where the player should rotate their body to the right and shift their weight to the back foot without changing the upper body position. Once the ball is near enough to the paddle, the player should strike the ball with the paddle. In this step, the player rotates their body to the left and forward while shifting their weight to the opposite foot. The angle of the paddle should be rotated forward slightly. The finishing position is the position of the player after striking the ball and following through. In the forehand maneuver, the paddle should move forwards and up. After reaching the finishing position, the hand and paddle must go back to the ready position so that the player is ready for the next ball.
- Backhand Drive The backhand drive's stance differs from the forehand drive in that the player's position is parallel to the edge of the table with both feet evenly placed. Otherwise, it is relatively similar to the forehand drive in that the feet separation and squat are the same. The player's arms should be in front of the player, and the elbows should be bent. During the backswing maneuver, only the upper body should move. The paddle should move towards the body above the hip opposite the dominant hand, and the paddle should be slightly angled towards the table. During the strike, the paddle moves forward and up, the elbow largely drives the movement. As in the forehand drive, the paddle should follow through the strike's direction during the finish. The arm should still be slightly bent. Afterward, the arm should return to the ready position.

Based on these instructions, we utilized a Vicon system with 20 cameras to obtain the professional trainer's smooth and polished motions. Then, we converted the captured motions to animations and used them as a predefined model (avatar) that participants need to mimic to learn the right playing posture. The training has both the essential playing maneuvers of forehand and backhand drives. In Fig. 4, (a)shows an example of a trainee's posture taken with the depth camera before training, and (b-e) show the correct posture of forehand and backhand ball returns by the professional trainer. We compare the trainee's postures and the professional trainer using the joint angles to determine if the trainee performs well. The upper-body posture is represented by α, β, γ, and δ angles while ϵ, ζ, and η represent the lower-body posture. At each time step during training, the trainee's joint angles are compared to the professional trainer's posture. We use a depth camera (Microsoft Kinect 2) to collect the skeletal information of the trainee in real-time and compare it to a professional trainer's pre-recorded movements in the VE. An error window of 10 degrees is used for angle comparison between the models.

The joint angles are shown on the feedback board as the trainee moves in real time, and three indicators showing whether they are performing the correct movements. There is an indicator for the upper-body (arms), another for the lower-body (squatting), and the third one for the whole posture. Colored indicators display how closely the trainee's posture and the model's match. If the trainee's joint angles are not within an acceptable range, the indicators are red, whereas if the joint angles are close to that of the avatar, the indicators are green.

The sign next to each angle in Fig. 4 determines if the trainee needs to increase or decrease the joint angle to perform the correct posture. For instance, before training, the angle between the legs ϵ is small because the user is standing upright. However, to perform the correct posture, the player needs to squat; therefore, the angle needs to increase. Similarly, all other angles either have (+) or (-) sign showing the change needed to perform the correct posture. Each angle color corresponds to the results presented later. Angles that are not colored were not assessed; in particular, all participants were right-handed, and since the dominant hand holds the racket, we ignored the non-dominant hand. θ represents the angle made between the paddle face and the table surface. The beginner players tend to hold the paddle so that the paddle's face makes a right angle with the table's surface, sending the ball high over the net. Since our goal is to return lower balls, the instructions are to lower the paddle toward the table to have a smaller angle.

The user (player) can move the avatar around; they can place it in front of them or bring it to where they are and mirror the movements. This gives the user the ability to observe the posture anywhere while seeing the angle comparison of the avatar and themselves on the feedback board. They can also pause the animation and see the instruction in

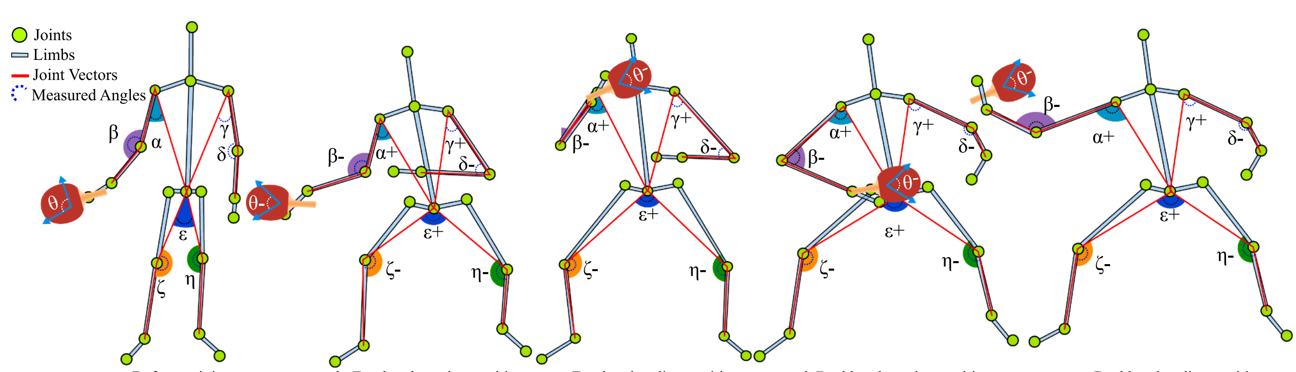

Fig. 4. (a) Trainees skeletal posture before training. (b-e) The postures are taken from the professional trainer and used as the gold standard for training feedback.

the other forms on the feedback board. The VRTT system stores all the raw data in real-time to regenerate the intended session for later data analysis. The stored data consists of the depth camera information and all paddle-ball-related data. We have developed a separate virtual environment (Data Generation Manager) to generate all the needed data, such as posture change over time and ball-paddle relationship data. Because the raw data is kept unchanged, any other desired data can be generated using the data generation manager. As shown in Fig. 2(c), the generated data is then fed to the Data Analysis System (DAS), which is a separate Python-based system to analyze the data. The DAS uses both the virtual environment data and manually collected data (questionnaires) to produce the final results. The operator has full control to analyze data based on group, individuals, type of exercise, type of measured data, and many more in-depth analysis options.

Paddle handling training consists of forehand, backhand, mixed (alternating forehand and backhand), and target exercises (mixed exercises where the player aims to return the ball to a specific side of the table). The player has full control over the ball and launcher parameters such as ball speed, spin, launching angle, number of the balls, and launching speed. Besides, there are a set of pre-configured training exercises that the player can use. We also developed a robotic opponent represented by a paddle to assist in training.

The feedback board is used to display dynamic information. During posture training, it shows the posture-related instructions that the user can navigate (Fig. 1). When the user practices the forehand and backhand drives, they can see the professional avatar in front of them and see the joint angles and posture indicators showing on the board. During ball returning exercise, the user sees the ball-related information such as speed, spin, collision angles, and the number of returned balls. We have designed the board to be rearranged and show the data to the user's liking to offer a dynamic feedback loop, so the user is aware of the exact situation of their playing style. The user can also choose not to see the feedback to avoid feeling overwhelmed.

4. Experimental design

We designed an experiment to evaluate our system's efficacy for motor learning by training a group of subjects for five VR training sessions. Fig. 2(b) shows the experimental design where the participants needed to go through five training sessions over three weeks, lasting 45 minutes each. The data were collected during the VR assessment sessions A1 and A5 before the first and after the fifth sessions to evaluate the performance. The data included skeletal information, ball-paddle information, and questionnaires given after the sessions. We compared data of both sessions for statistical analysis. Since we only had one group and two dependent data collection points (baseline and retention), we used parametric paired-samples t-tests for statistical analysis to show the difference between pre-training and post-training data, representing the within-subjects training effect. The non-parametric Wilcoxon signed-rank tests were used in cases where normality or homogeneity of variance assumptions were not met. We used the Shapiro-Wilk test for normality and Levene's test for homogeneity of variances. Generally, parametric tests more lead to the rejection of a null hypothesis. In contrast, non-parametric tests are more robust, yet provide more conservative estimates than parametric tests.

We acquired approval from the Institutional Review Board (IRB) of the University of Colorado Denver before recruiting subjects for this study. We recruited nine subjects (four females and five males) with no experience in table tennis on the university campus via flyers and emails. During the recruitment process and before the study started, we emphasized the inclusion and exclusion criteria. The participants had to have no experience in table tennis and not be active playing other sports that include playing balls by hands of any sort. We wanted to prevent any other training factors that might affect the study in any possible way. The participants were between 18 to 30 years of age, and all of them were right-handed. Before the experiment started, the participants signed a consent form that detailed the study's purpose, inclusion and exclusion criteria, potential benefits, and potential risks.

The depth camera was placed in front of the player (2 m away and 1 m above the ground) at the beginning of each session and calibrated to be aligned with the virtual environment. We asked the participants to read the instructions provided on the feedback board in the VE. The instructions included the correct forehand and backhand postures, the right way of holding the paddle, and how to return faster and lower balls. After reading the instructions, we asked the participants to practice the postures and techniques detailed in the instructions. After posture training, the participants were asked to practice ball returning with forehand drive, backhand drive, mixed and targeted ball exercises. The lead researcher gave some feedback regarding the posture and paddle holding instructions when the participants had questions. The lead researcher also guided participants on using the system correctly and made sure they are comfortable using the headset. It's worth mentioning that the feedback purpose was only for correct system usage and wasn't part of the experiment. In the fourth session, the participants were asked to play with the robotic opponent and use an HTC Vive controller instead of the paddle to provide subjective feedback comparing natural grip and haptic feedback.

We used the collected data in VR assessment sessions A1 and A5 to assess the participants' performance. We assessed the participants' posture by analyzing each technique's joint angles (forehand and backhand) individually. We examined the changes in joint angles for each extremity except for the left arm because all of our participants were right-handed. Some joint angles needed to decrease from an untrained position to move towards improved posture, whereas some joint angles needed to increase as shown in Fig. 4. The skeletal poses shown in the figures are the starting and ending poses for the techniques during training; we defined the starting posture as the pose of the player when the ball is launched, and the ending posture as the pose of the player when the paddle reached the highest point after returning the ball. We took the average of all the participants' data to determine the average improvement of posture and returning technique. In this study, we broadly calculated body posture to include starting and finishing positions to show the learning process. However, more granularity is needed for more detailed analysis as most existing work divides the movement into four phases (Wong et al., 2020).

We calculated paddle controlling and maneuvering to assess the paddle handling training. The controlling angle refers to how the trainee held the paddle while waiting for the ball (from when it's launched until the ball is hit), while the hitting angle refers to the moment the ball is hit. Generally, beginner players tend to hold the paddle so that the paddle's face makes an approximately 90-degree angle with the table surface, resulting in a higher ball trajectory and slower ball speeds. Therefore, measuring this behavior would show their learning progress. We also calculated hitting paddle angle, paddle speed, ball speed, spin, and average ball height.

After collecting data in VE, we surveyed the participants regarding the VR system on physics, haptic, audio, visuals, and the realistic representation of each simulation. The questionnaire had 18 questions using a Likert scale ranging from 1 to 5 (least satisfied to most satisfied), each with a comment section for additional qualitative feedback. The participants were encouraged to write detailed feedback to have subjective results in addition to the objective measurements. The first 7 questions were related to self-assessment regarding how confident they feel playing table tennis, and the other 11 questions were related to the VR system.

5. Results

5.1. Posture

Fig. 5 shows the average joint angles for forehand drive before and after training for both starting and finishing positions. The VR training

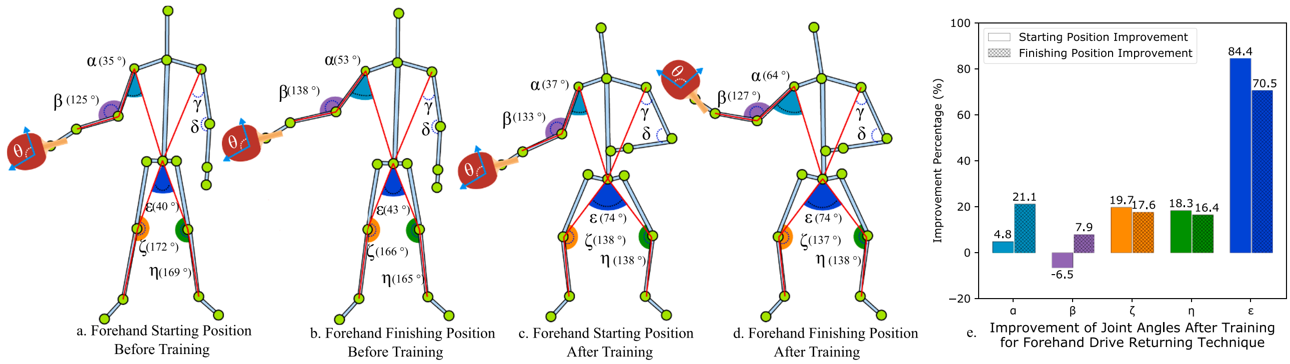

Fig. 5. Forehand posture (a-b) show joint angle values for starting and finishing position before and after training. (e) shows the amount of change in which each bar color corresponds to a joint angle with the same color.

instructed participants to squat as shown in Fig. 4 and place their right foot forward for stance. However, in this data presentation, the skeleton is flattened to show the exact angles in two dimensions. Because of that, the upper-body and lower-body appear to be in the same line, while in the actual three-dimensional skeletal data, they are more similar to Fig. 4. Sub-figures (a) and (b) show the starting and finishing positions of the forehand drive before training with corresponding angles for each joint, while the sub-figures (c) and (d) show the starting and finishing positions of the forehand drive after training. Sub-figure (e) shows the change in angle for each joint. Fig. 6 shows the average joint angles for the backhand drive before and after training for both starting and finishing positions. For the backhand drive, the player needed to squat lower to return balls at a lower trajectory and increase the ball speed and spin.

Since the players' stance did not change during the starting and finishing positions, we can see the lower-body changes are almost stable. This contrasts with the upper body, where the shoulder and elbow joints' angles changed noticeably between the starting and finishing positions. The only negative joint angle change was the elbow joint angle during the forehand starting position, where the joint angle was closer to the gold standard before training. The big changes occurred in lower-body angles were because beginner players did not squat naturally. Additionally, they tended to place their arms close to the torso and had an open elbow angle. However, after training, the arm was further away from the torso, and the elbow joint had a smaller angle at the finishing position. Even though the skeleton was drawn in the same depth level, the similarity between the player's post-training posture and the professional posture is evident.

5.2. Paddle and ball

Fig. 7 shows the data for paddle controlling and hitting. The paddle controlling angle decreased from 94 degrees to 69 degrees which represents a 26.5% improvement. At the same time, the hitting angle decreased from 104 degrees to 85 degrees representing an 18.5% improvement. The data show that both the controlling and hitting angles are smaller in values after training. This shows that the trainees learned to keep the paddle face rotated more towards the table and be in a good position before hitting the ball. Another important skill participants learned is how to swing that paddle faster to return faster balls and apply spin. The paddle speed was only 1.8 m/s before the training, while this number increased to 3.67 m/s after training which counts for 105.7% improvement.

The presented results show that the participants learned both posture and ball return techniques, but they don't tell us how these learned skills affect ball flight trajectory. If the measurements had moved towards the gold standard measurement, it should be evident in the ball return quality. Therefore, we examined the ball flight quality (ball speed and height) improvement after training. Fig. 8 (a) shows ball speed before and after training. On average, the ball's speed at the moment when it hit by the paddle increased from 6.12 m/s before training to 8.7 m/s after training, which is a 42.1% improvement. Fig. 8 (b) shows ball height. The average ball height during a return was 0.31 m before training, which lowered to 0.18 m after training, a 42.2% improvement. In contrast, as shown in Fig. 8 (c), the number of returned balls decreased from an average of 26 balls before training to 17 balls after training, representing a 33.2% decrease. This was an expected result due to a learning curve where participants had to unlearn a "ping-pong" playing style and learn professional techniques. Although the ball count

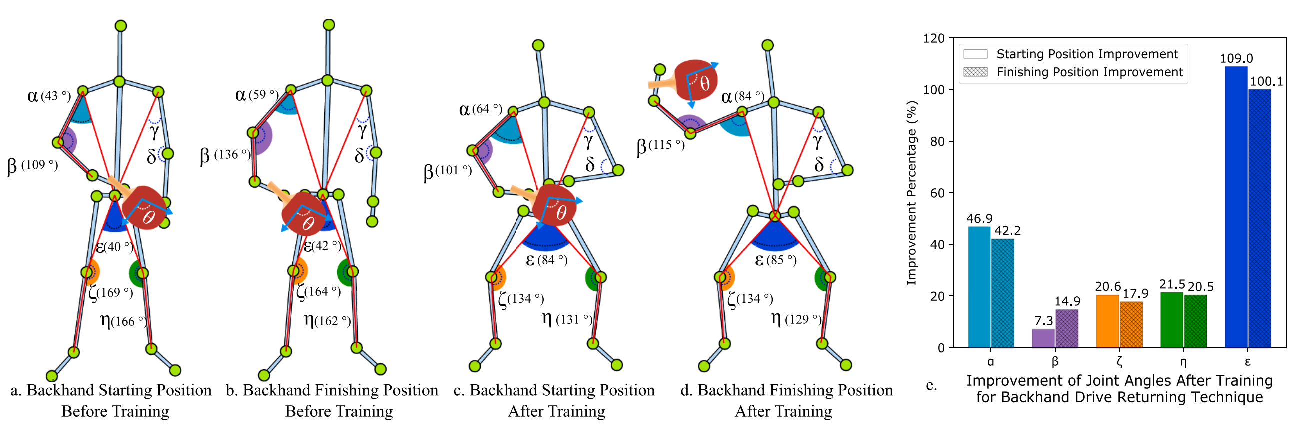

Fig. 6. Backhand posture (a-b) show joint angle values for starting and finishing positions before and after training. (e) shows the amount of change where each bar color corresponds to a joint angle with the same color.

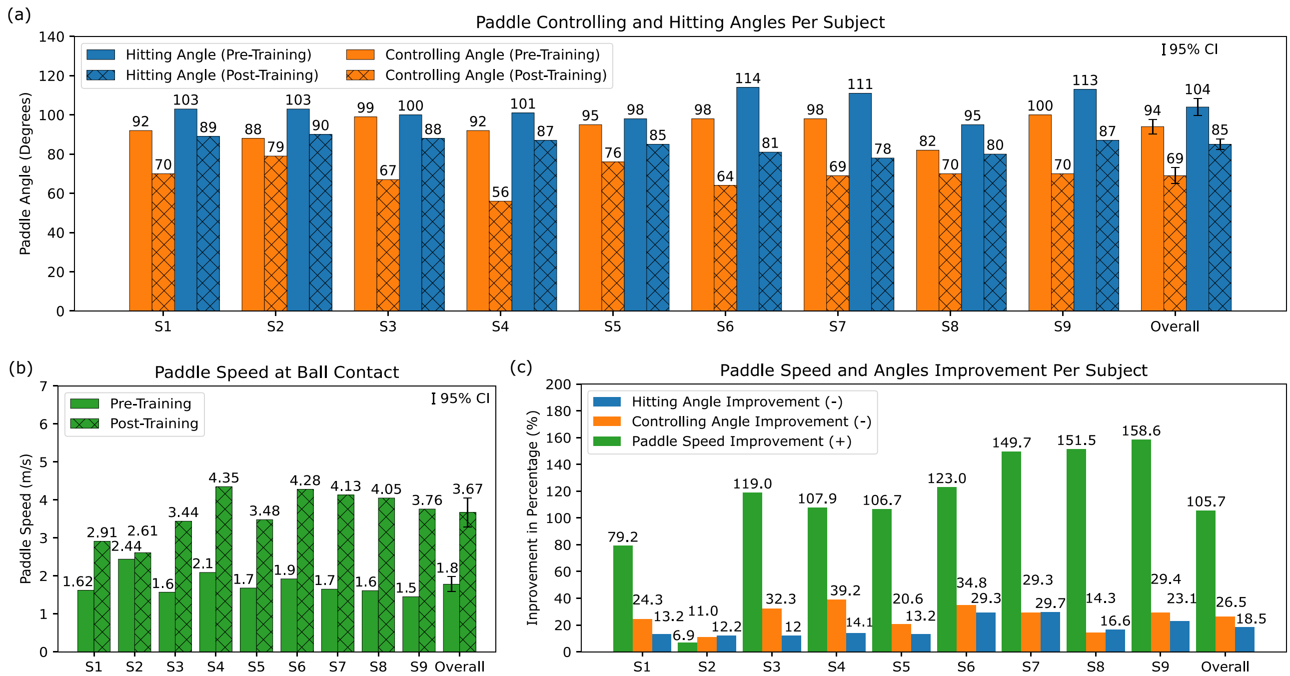

Fig. 7. Paddle handling angles and speed before and after training. In (a), the controlling angle is the average paddle angle change while waiting for the ball. (b) shows the paddle speed when the ball is hit. Each bar color represents the improvement of the corresponding bar color in a and b.

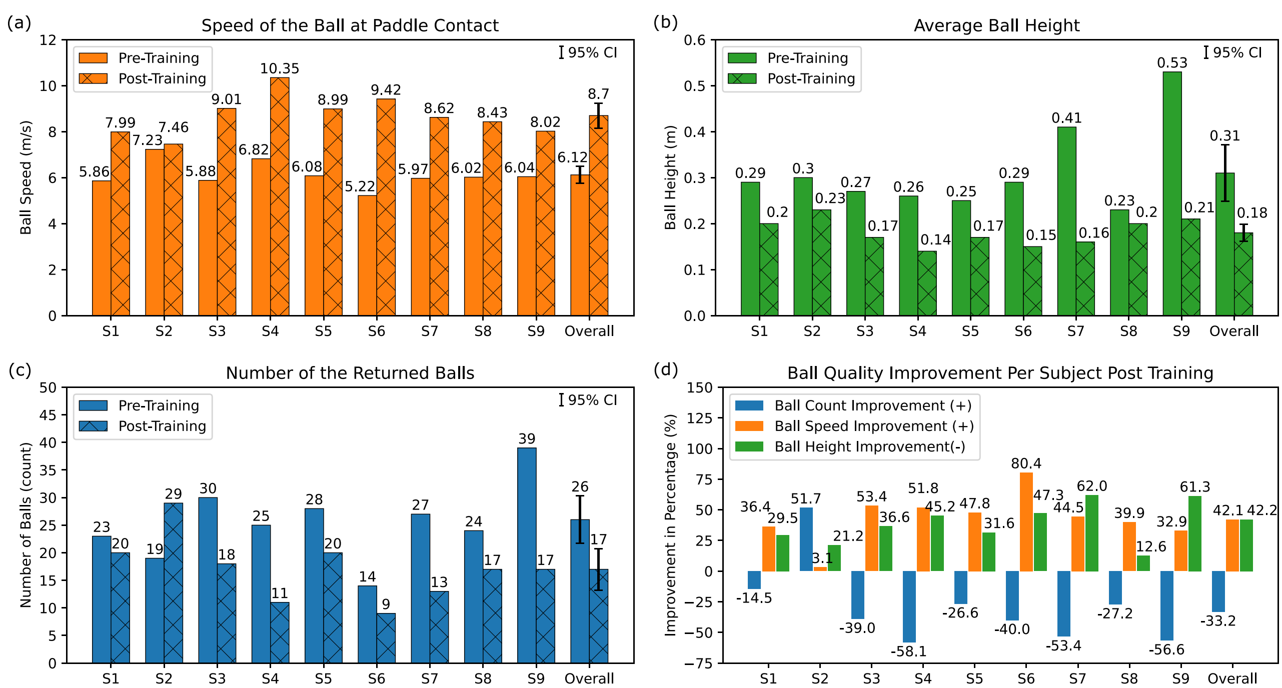

Fig. 8. (a-c) Ball quality of ball speed, ball height, and the number of returned balls. (d) ball quality improvement, each color is corresponding to sub-figure a, b and c.

decreased, the ball quality improvement reflects an important change, as will be shown in the hypotheses testing section. Additionally, the ball spin, which has a critical impact on the ball trajectory, improved greatly. The ball spin increased from 1.55 radians/s to 3.38 radians/s, which is a 118% increase. This change is directly related to the paddle speed and the hitting angle, which are outcomes of a better posture; when the participants squat and the returning angle is smaller, it requires faster paddle speeds. We clearly see that good posture, paddle control over the returning angle, and speed led to faster and lower balls. Furthermore, as seen in the angle between the legs, participants lowered their torso to hit lower balls. We calculated the Center of Mass (COM) based on the method presented in Oagaz et al. (2018) to show the torso has lowered, which required the players to squat and push their chest forward to maintain balance. The data shows that participants' COM lowered by 6.3% from 0.95 m to 0.89 m (the average height of the participants is 1.75 m).

5.3. Questionnaire

To analyze the quantitative composite score results from the questionnaires, we averaged the participants' answers to represent their overall self-confidence and satisfaction with the VR system. The results from the first seven questions regarding the confidence level show an increase by 31% from 2.85 points (out of 5) in session A1 to 3.74 points in session A5. The other 11 questions regarding the VR system show that the score increased from 4.18 points to 4.4 points, which is a 6% improvement. Additionally, the comments from the participants were generally positive, such as: *"I felt deeply involved, the environment felt mostly realistic, and I felt that I could control the paddle accurately.", "I feel more confident in my skills and overall improvement. Hand-eye coordination is better. Consistent returns and posture techniques helped my overall play style."*. Other comments referred to how the system taught them correct posture and paddle controlling, how the VR environment made it easier to focus on learning table tennis since there were no distractions, and how the audio feedback helped compensate for the lack of haptic feedback when using the racket. More critical comments mentioned how the headset's Field of View (FOV) made it more difficult to return balls and that the headset cable was distracting.

5.4. Hypotheses testing

A set of paired-samples t-tests with the significance level of alpha = 0.05 was conducted to compare posture before and after training. Since we measured the posture using joint angles, we conducted the tests for each joint angle separately for both forehand drive and backhand drive and both the starting and finishing positions. We used the Wilcoxon tests instead of t-tests if either normality or homogeneity of variances was violated. However, if the assumptions were met, *t*-test results are reported because the parametric tests are more able to reject a null hypothesis as mentioned before. Table 1 shows the results for the forehand posture. There was a significant difference in the scores for lower-body joint angles before and after the training for both starting and finishing positions. The data shows no significant difference between shoulder and elbow angles for the starting position. However, there is a significant difference for the ending position.

In all cases, both normality and homogeneity of variances assumptions were met to perform t-tests except for the left knee angle (η) in the finishing position that the normality assumption was violated. Therefore, we conducted a non-parametric Wilcoxon singed-rank test. The test results show that the difference is significant, pre-training angle (*Mdn* = 167.32) decreased in post-training (*Mdn* = 137.33); $T= 0$, $z = -2.67$, $p = 0.003$. These results suggest that VR training helped the participants to have better posture for both starting and finishing positions for forehand drive returns. The results also suggest that participants had a similar forearm placement for the starting position before training but not for the finishing position. However, the stance improved significantly for both the starting and finishing positions. Overall, the results support H1 that states that the posture will improve significantly after five training sessions in VR.

We repeated the same process for the backhand drive returning posture. Table 2 shows the results of the t-tests for the starting and finishing positions. The results suggest that the starting position improved significantly for all angles except the elbow angle, which means that the participants' elbow angle before and after training was similar. The results also indicate that the overall finishing position changed significantly after training. These results also support H1. Additionally, the results of Wilcoxon test showed no significant differences in the scores for COM pre-training (*Mdn* = 0.92) and post-training (*Mdn* = 0.89); $T = 7$, $z = -1.84$, $p = 0.074$. Even though the results are not significant, they show that the participants lowered their COM to produce lower ball trajectories.

For paddle handling techniques, we conducted a set of Wilcoxon signed-rank tests to compare before and after training conditions. We decided to use non-parametric analysis for all measurements for consistency purposes due to parametric assumption violations for three measurements. There was a significant difference in the scores for the average paddle angle during the ball waiting time pre-training (*Mdn* = 102.53) and post-training (*Mdn* = 86.96); $T = 0$, $z = -2.67$, $p = 0.004$. There was a significant difference in paddle angle when the ball is hit from pre-training (*Mdn* = 95.32) and post-training (*Mdn* = 69.82); $T = 0$, $z = -2.67$, $p = 0.004$. Besides having a lower paddle hitting angle, the *SD* decreased from 6.95 to 4.36, suggesting more paddle handling consistency. The existing work supports this notion that higher-level players

Table 1
Backhand drive joint angles paired *t* test results.

Joint Measurement	Pre-Training		Post-Training		Paired *t* test		
	Mean	Std Dev	Mean	Std Dev	t value	df	p (two-tailed)
Forehand drive starting position							
Shoulder angle (α)	35.66	4.76	37.36	7.15	-0.69	8	0.507
Elbow angle (β)	125.55	13.44	133.73	19.93	-1.14	8	0.286
Right knee angle (ζ)	172.20	3.26	138.20	15.55	7.1	8	< 0.001
Left knee angle (η)	169.31	6.52	138.34	10.52	10.39	8	< 0.001
Between-legs angle (ϵ)	40.33	9.47	74.39	10.27	-8.21	8	< 0.001
Forehand drive finishing position							
Shoulder angle (α)	53.42	12.05	64.72	15.82	-2.49	8	0.037
Elbow angle (β)	138.71	13.87	127.75	10.17	2.46	8	0.038
Right knee angle (ζ)	166.57	10.05	137.27	17.51	5.42	8	< 0.001
Left knee angle (η)	165.64	9.70	138.42	11.23	Wilcoxon conducted		
Between-legs angle (ϵ)	43.47	11.61	74.11	10.34	-7.46	8	< 0.001

Table 2
Backhand drive joint angles paired *t* test results.

Joint Measurement	Pre-Training		Post-Training		Paired *t* test		
	Mean	Std Dev	Mean	Std Dev	t value	df	p (two-tailed)
Backhand drive starting position							
Shoulder angle (α)	43.63	8.32	64.08	10.37	-6.26	8	< 0.001
Elbow angle (β)	109.98	12.09	101.96	13.26	1.33	8	0.218
Right knee angle (ζ)	169.82	4.25	134.80	7.18	14.47	8	< 0.001
Left knee angle (η)	166.95	14.80	131.09	8.66	7.97	8	< 0.001
Between-legs angle (ϵ)	40.51	8.20	84.68	11.65	-12.70	8	< 0.001
Backhand drive finishing position							
Shoulder angle (α)	59.38	14.74	84.47	14.85	-4.51	8	0.002
Elbow angle (β)	136.16	18.18	115.86	16.36	3.08	8	0.015
Right knee angle (ζ)	164.03	12.73	134.61	9.11	5.94	8	< 0.001
Left knee angle (η)	162.84	18.70	129.48	9.54	6.03	8	< 0.001
Between-legs angle (ϵ)	42.54	11.67	85.14	11.78	-11.31	8	< 0.001

tend to maintain a similar paddle angle at ball impact (Iino et al., 2017). There was also a significant difference in paddle speed at the hitting point from pre-training (*Mdn* = 1.65) to post-training (*Mdn* = 3.76); T = 0, z = -2.67, p = 0.004. The paddle controlling and hitting results suggest that the participants' paddle maneuvering significantly improved after VR training. Thus, the results support H2 that states the paddle maneuvering will improve significantly after five sessions of VR training.

If the forehand and backhand drive returning stance, arm movements, and paddle handling significantly improved, we expect to see improvement in ball trajectory. The results show a significant difference in the ball speed between pre-training (*Mdn* = 6.02) and post-training (*Mdn* = 8.62); T = 0, z = -2.67, p = 0.004. The results also show a significant difference in the ball spin between pre-training (*Mdn* = 1.34) and post-training (*Mdn* = 3.20); T = 0, z = -2.67, p = 0.004. There was a significant difference in the average ball height from pre-training (*Mdn* = 0.29) and post-training (*Mdn* = 0.17); T = 0, z = -2.67, p = 0.004.The results suggest that the ball quality has improved significantly. Specifically, the results suggest that ball trajectory and speed improved due to improved posture and technique. In contrast, the number of returned balls significantly decreased between pre-training (*Mdn* = 25.38) and post-training (*Mdn* = 17.38); T = 5, z = -2.67, p = 0.039. This was predictable as the participants went through a learning curve and were also instructed to focus on the ball trajectory and speed rather than the number of returned balls.

The results from the first seven questions in the questionnaire regarding the confidence level significantly increased from pre-training (M = 2.85, SD = 0.63) to post-training(M = 3.74, SD = 0.51); $t(8)$ = -4.10, p = 0.003. Even though there was a 6% improvement in the participants' evaluation of the system (the other 11 questions), no significant difference was found in pre-training (M = 4.18, SD = 0.43) and post-training (M = 4.39, SD = 0.35); $t(8)$ = -1.13, p = 0.289. The average overall rating of 4.39 on a scale of 5 points indicates that the participants enjoyed the system and were comfortable using it.

6. Discussion

The results showed that all joint angles improved in accuracy except for the elbow angle, which remained relatively the same. This could be attributed to the participants already having a naturally good elbow posture before training, or possibly to a lack of attention to the elbow posture when focusing on paddle handling. Figs. 5 and 5 do show the elbow changing in position and orientation, but this is due to a drastic improvement in the shoulder angle. However, after examining the recorded skeletal data for the forehand drive, it appeared that the subjects tended to perform the correct movement with a small delay, which would have affected the comparison with the avatar. Variations in individual playing styles and bodily characteristics may have played a role in this as well. Despite a lack of improvement in the elbow joint, this study's results suggest that the efficacy of VR for learning crucial motor skills in table tennis is exemplary.

Though posture and paddle handling generally improved overall, the results also show a significant decrease in the returned ball count. As mentioned in the Introduction section, this was expected due to participants undergoing a learning curve and was not the focus of the study. However, with more training sessions, it's expected that the number of returned balls will also increase. For any generalization of this system's efficacy for table tennis training in the future, the experiment design must include more training sessions for better outcomes in both quality and quantity of returned balls.

The confidence in data interpretation and validity of the hypotheses greatly depends on ensuring that the study is sufficiently powered. Therefore, we performed a post hoc statistical power analysis for all the conducted paired-samples t-tests and Wilcoxon signed-rank tests using Gpower software for validating the sample size. We used the recommended power level of 0.80 and alpha of 0.05 to interpret the outcome. We evaluated all the aspects of the performance improvement of posture (joint angles), paddle controlling (paddle angles), and ball measurements. The results showed that for the 28 measurements we calculated in the Results section, only 6 were underpowered. The statistical power of α and β in both forehand starting and finishing positions, β of backhand finishing position and COM were 0.08, 0.29, 0.69, 0.75, 0.24 and 0.69 respectively. The average power for the other 22 measurements was 0.97. The reason for such high power despite the modest sample size is the big effect size of the training and the nature of the data. For instance, some joint angles changed significantly by simple movements. The fact that all the subjects improved contributed to this too, which is why Wilcoxon tests' results are similar for several measurements presented in the Hypothesis Testing section. The effect size and the statistical power will be more balanced by having a more diverse and bigger sample size. Finally, limited statistical power because of the modest sample size in the present study (n = 9) may have played a role in limiting the significance of some of the statistical comparisons conducted. A post hoc power analysis revealed considering medium effect size (d = 0.5), we would need an n of approximately 34 to obtain statistical power at the recommended 0.80 level. For a large effect size (d = 0.8) as present in this study and statistical power of 0.95, we would need 23 subjects.

Defining good posture for table tennis is not straightforward, as playing poses can be affected by gender, body shape and body size (Bańkosz et al., 2020; Ren et al., 2019). For the sake of simplicity, we chose to train our subject population to learn the same "right" beginner playing techniques (forehand and backhand drives) regardless of their demographics. However, for these types of training platforms to be generalized and used for training purposes, we should incorporate various playing techniques and styles from numerous professional players into the system. Additionally, the exercises could be tailored toward individuals using advanced approaches such as adaptive feedback and machine learning to accommodate the needs of a larger and more diverse population.

The accurate and smooth avatar animations used to train posture and techniques were recorded using a Vicon tracking system. Though the accuracy and fast movement tracking of this tracking system would have provided ideal results for kinematic analysis of participants, the necessary calibration and fitting process of a specialty suit with optical sensors for this system limits the broader user study. The time, effort, and resources needed to capture user's real-time movements with this system would make carrying out this study with a decent sample size infeasible. For these reasons, we chose to use the Microsoft Kinect 2, which is a more convenient and unobtrusive sensor. Although the Kinect is effective for various sports and games (Crecente, 2013), it presents challenges for fast movement tracking and is not designed for thorough and accurate kinematics evaluation. Furthermore, the participants' clothing and body orientation toward the camera may introduce some inaccuracy in joint angle measurements. Despite these limitations, the camera's accuracy and speed were high enough for our purposes, as the system is designed for beginner players with slower movements. In addition to the Kinect's remote detection and ease of use, the Kinect is also low-cost, making it more accessible and removing barriers to adoption. As presented in the Results section, we successfully used the data captured by Kinect to direct the trainees to correct their posture and generate significantly better posture, techniques, and ball outcomes.

Racket handling is a fundamental component of a player's technique, and the racket used in the VE must resemble a real racket. Though the racket grip and weight are similar to a real racket in our system, the weight distribution is different due to the tracker weight. This could make handling the racket feel unnatural, but participants' feedback regarding the racket was positive. Because this study covers only training in VR and not skill transfer to the real-life sport, subtle disparities between the virtual racket and a real racket such as weight distribution and rubber quality were not of concern for this study, but would need to be accounted for in studies involving skill transfer or for generalized use of the training platform.

The ball behavior in the VE is also of critical importance and relies heavily on the simulation of ball spin. In our simulation, we implemented spin based on equations of known forces acting on the ball. However, due to hardware limitations, we did not validate ball spin explicitly. The inconsistency of spin and speed produced by most ball launchers (including the Huipang HP-07) due to manual controlling makes it challenging to set up a controlled environment to generate cases specifically for spin validation. However, a high-speed, high-resolution camera with a highly accurate ball launcher could capture spin changes. Even though we didn't validate spin separately, we can infer from the ball flight validation results (Fig. 3(b)) that the ball accurately rebounds off the table, showing a realistic transmission of energy and spin between the ball and the table. Additionally, the coefficient of restitution in the VE, which relies on correct spin simulation, showed an accuracy of 99.76%. The subjective feedback from the professional trainer and the participants also indicated that the ball's behavior was realistic; as one participant reported, *"The ball flight and physics appeared natural to me."*.

In future work, we plan to investigate table tennis's learning curve in VR by having multiple groups, each with different training sessions. We're also interested in exploring questions of skill transferability and VR training effectiveness compared to real-life training as this study focuses on learning motor skills in VR only. The broader future goal in developing this system is to create a tool that would allow us to investigate the motor learning process in VR and determine what components are most important for effective learning. Many important questions remain on this front, such as what hardware specifications and what level of physics simulations are enough to provide the same level of realness as the real training? What aspects of virtual training are necessary, and what are secondary? If these questions are appropriately addressed, they could enable the development of more effective VR training systems for various domains.

7. Conclusion

This paper has demonstrated the unique ability of VR's real-time feedback to promote the learning of fine-grained motor skills necessary to perform common table tennis maneuvers correctly. We have developed a VR table tennis system that trains beginner players by providing real-time feedback on posture and technique. The system provides a realistic table tennis environment with near-real ball flight and collision behaviors. We have validated our system by demonstrating that the nine recruited beginner players had significant changes in posture and technique after five training sessions with the system. We also showed that learning correct posture and technique leads to an immediate improvement in ball quality outcomes. Besides showing our system's efficacy for motor learning, this work offers a low-cost, remotely accessible, and beginner-friendly VR table tennis training platform. In this study, we only covered motor learning in VR specifically, not skill transfer to real-world performance or VR training effectiveness compared to the real training. In the future, we plan to use this system to investigate the learning process to determine which variables make the most significant difference in learning outcomes. Furthermore, our outcomes can be used to allow further investigation into training transfer from VR to real-world performance and compare VR training to real training.

CRediT authorship contribution statement

Hawkar Oagaz: Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Formal analysis, Writing – original draft. **Breawn Schoun:** Conceptualization, Resources, Writing – review & editing. **Min-Hyung Choi:** Conceptualization, Investigation, Methodology, Resources, Project administration, Funding acquisition, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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