第 24 回日本バーチャルリアリティ学会大会論文集（2019 年 9 月）

Prediction of Ping-Pong Ball Trajectory Based on Neural Network Using Player's Body Motions

Ping-Pong Ball Tracking for Prediction of Its Trajectory with Neural Network Based on Player's Body Motions

Jianyu Chen [1], Tao Morisaki [1], Ansheng Wang [1]
Masahiro Fujiwara[1], Yasutoshi Makino[1) 2)], and Hiroyuki Shinoda[1]

1) 東京大学 新領域創成科学研究科 （〒277-8561 千葉県柏市柏の葉 5-1-5）
2) JST PRESTO

In order to make table tennis more interesting, in this study, we try to use neural network with player's body motions to predict the trajectory of table tennis ball faster than real time. Because of the characteristics of table tennis, such as the rotation which cannot be recognize by the camera, it is difficult to predict the trajectory. In this paper, we propose to use the player's skeleton data to analyze the influence of table tennis rotation. Furthermore, we use two high-speed cameras to record the three-dimensional trajectory data of table tennis.

Keyword : Ping-pong, prediction, neural network

1. Introduction

In recent years, with the development of machine learning, using body motion information to predict the future in a short time has been proposed. The prediction of jumping and walking has been realized [1], and the prediction of trajectory of tossed ball in volleyball [2] and punch motions in boxing [3] have also been reported. As one of the goals of using body movements to predict the future, in this study, we focus on predicting the trajectory of a ping-pong ball (PPB). Table tennis games take up relatively small space, thus we can easily project images on the table like Ping Pong++ [4] as AR application. At this point, it is desirable to predict the trajectory of the ball correctly to superimpose the images. When the ball is in the air, it usually makes a parabolic motion, therefore it is not too difficult to predict its trajectory. By contrast, when the ball touches the table, especially with strong rotation, the trajectory will become unpredictable. Because a PPB is a monochrome object, the rotational direction of the ball cannot captured only by a camera. Therefore, in this study, we focus on the player's body movements. When a specific rotation is given to the ball, the corresponding body movements will change accordingly. By measuring those movements, it is possible to predict the trajectory of the ball after it rebounds off the table.

Predicting the trajectory after the rebound may have many practical applications. For example, projecting the predicted position to beginners beforehand will make them learn better. People who watch table tennis games will also have a better experience. Additionally, the player can know the opponent's response in advance when they take actions.

This paper is still in the initial stage of predicting the trajectory of the PPB. The system that is able to track the PPB's trajectory and capture human motion simultaneously has been completed. In the following section, we will introduce how the system works including the process of experiment.

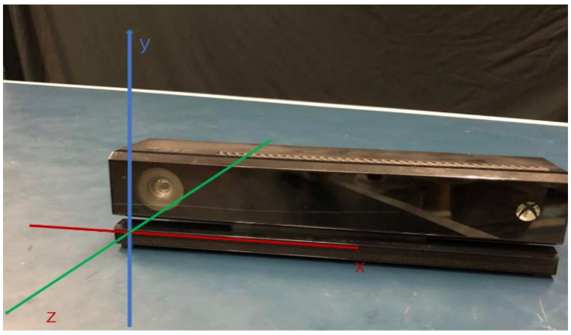

Figure 1 KinectV2

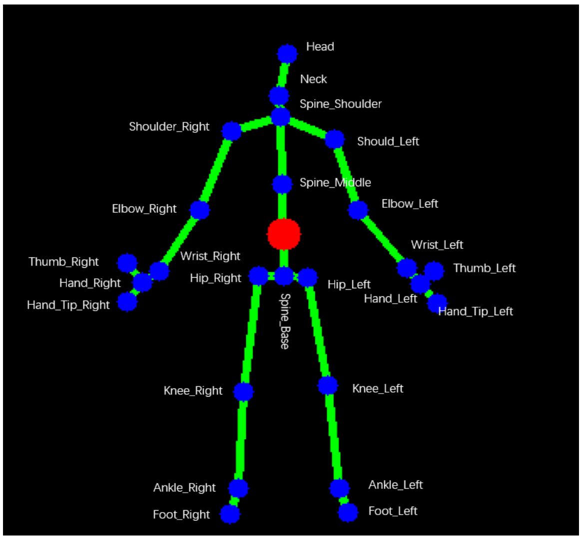

Figure 2 25 point skeleton

2. Experiment

2.1 Detecting a player's motion

In the experiment, we used a depth camera (KinectV2, shown in Figure 1) to detect human body motion. The depth camera measures three-dimensional human skeleton data at 25 points (Figure 2) in real time. All the motions of a player were collected with a frame rate of 30 fps.

2.2 Tracking trajectory of ping-pong ball

The trajectory of a ping-pong ball is detected by two calibrated high-speed cameras (XIMEA MQ003CG-CM, shown in Figure 3). The high-speed cameras take a picture with the maximum frame rate of 600 fps. The maximum frame rate is sufficient for the speed of a PPB in a standard table tennis game.

We used color tracking to track the ball. First, the high-speed cameras took a picture of a PPB shown in Figure 4. Second, processing by orange color filter, then the PPB was detected (Figure 5). Finally, we used triangulation to calculate the three-dimensional data of the PPB by the two-dimensional coordinates which got from the two cameras.

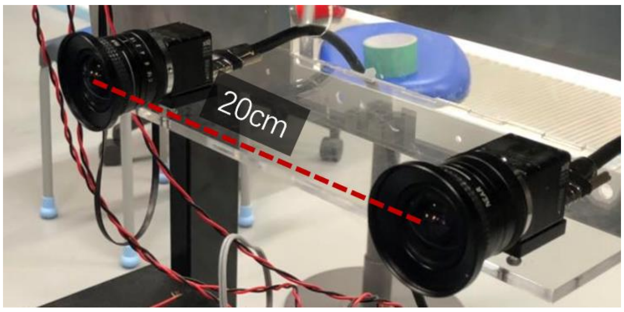

Figure 3 XIMEA

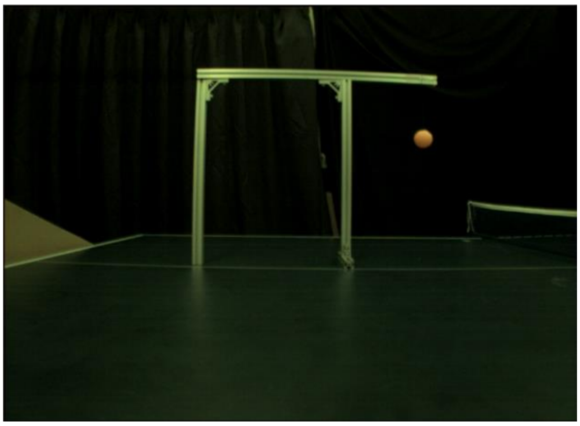

Figure 4 Original ping-pong ball picture

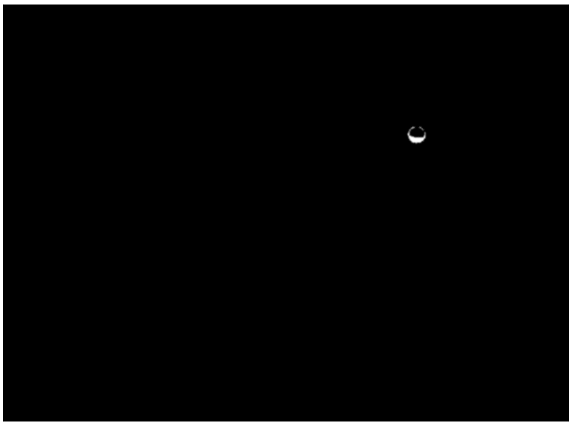

Figure 5 The ball after color filtering

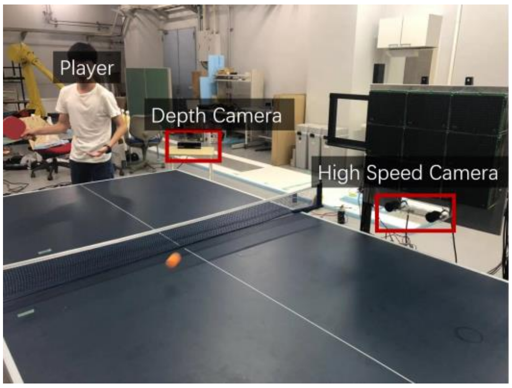

Figure 6 Collecting data

第 24 回日本バーチャルリアリティ学会大会論文集（2019 年 9 月）

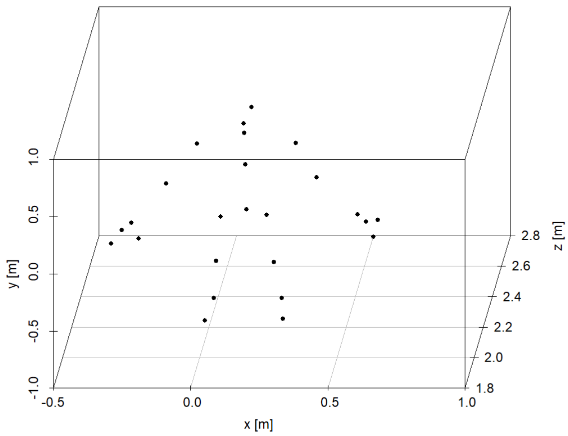

Figure 7 Three-dimensional Skeleton data

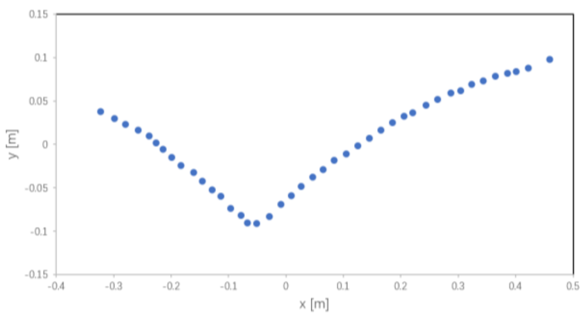

Figure 8 XY plane parallel to camera

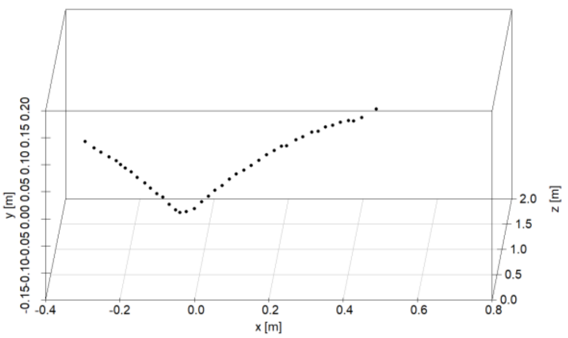

Figure 9 Three-dimensional trajectory of PPB

2.3 Collecting data

The experimenter stand on the end of the table, at the same time, Kinect collected skeleton data behind him. In the experiment, the experimenter served as a normal table tennis match, while XIMEA collected trajectory data of the ball from side of the table (Figure 6). In the work, we collected 5 sets of data, and each set served 50 times (5s served once). Therefore, we got 250 serves data which total usage time is 1250s (each set cost 250s).

3. Result

After the above steps, we can identify the players' movements in 30 fps. One frame of skeleton data is shown in Figure 7.

The three-dimensional data and two-dimensional data of the trajectory of the PPB are shown in Figure 8 and Figure 9. In this time, 42 frames of data were taken by the high speed camera in 0.271s (155 fps). As the length of the table is 2.74m, the speed of the ball was 5.0 m/s.

4. Discussion

In the experiment, we tracked the PPB in 155 fps is enough to record the trajectory which can be used in neural network.

Another question is that we used two computers to record the data of the depth camera and the high speed camera, as a result, the time of the output data was not the synchronize. Besides, the different in fps of these two cameras will be a problem. We will develop another programme to solve it. We will also develop and train a neural network to achieve the goal that predict ball trajectory when it bounces on the table.

Acknowledgement

This research is supported by JST PRESTO 17939983

References

[1] Yuuki Horiuchi, Yasutoshi Makino, and Hiroyuki Shinoda. “Computational Foresight: Forecasting Human Body Motion in Real-time for Reducing Delays in Interactive System,” ISS ’17, Pages 312-317 Oct. 17-20, 2017, Brighton, United Kingdom.

[2] Shuya Suda, Yuuki Horiuchi, Yasutoshi Makino, and Hiroyuki Shinoda. “Prediction of Volleyball Trajectory Using Skeletal Motions of Setter Player”, Proceedings of the 10th Augmented Human International Conference 2019, Article No. 16, Reims, France — March 11 - 12, 2019.

[3] Erwin Wu, Hideki Koike, "FuturePose - Mixed Reality Martial Arts Training Using Real-Time 3D Human Pose Forecasting With a RGB Camera", 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), Waikoloa Village, HI, USA, Jan. 7-11, 2019

[4] Xiao Xiao, Michael S. Bernstein, Lining Yao, David Lakatos, “Ping Pong++: Community customization in games and entertainment”, Proceedings of the 8th International Conference on Advances in Computer Entertainment Technology, ACE 2011, Lisbon, Portugal, November 8-11, 2011