Feasibility Study on Using AI and VR for Decision-Making Training of Basketball Players

Wan-Lun Tsai, Li-Wen Su, Tsai-Yen Ko, Tse-Yu Pan, *Member, IEEE*, and Min-Chun Hu, *Member, IEEE*

***Abstract*—Decision-making plays an essential role in basketball offense. Offensive players must make effective decisions to score a basket in various defensive situations. Virtual reality (VR) has been widely used in the training of athletes to strengthen their ability to make optimal decisions by creating controllable repeatable training scenarios. In this article, an action-aware offensive decision-making training system for basketball using VR and artificial intelligence is proposed. The proposed system is composed of different virtual defensive scenarios and an offensive action recognition framework. Trainees wearing head-mounted display and a motion capture suit are trained by intuitively interacting with the VR system and receive decision suggestions when a bad one is made. This study changes the training media and methods to create an immersive training environment during the training phase and evaluates the training effectiveness. These training scenarios are a conventional tactics board, the proposed VR system with a prerecorded 360° panorama video, and the VR system with computer-simulated virtual content. Results indicate that the training scenario affects the training in terms of decision time.**

***Index Terms*—Decision-making, sports, training, virtual reality (VR).**

I. Introduction

The utilization of emerging technology in the training of athletes has become a common tool, which makes the training more effective. Despite the motor skills training, cognitive training is also benefited from the use of virtual reality (VR), and the ability to create controllable repeatable situations makes it possible to improve athletes' abilities without exorbitant costs [1]–[3].

Manuscript received April 6, 2020; revised May 30, 2021 and November 15, 2021; accepted January 16, 2022. Date of publication January 25, 2022; date of current version April 13, 2022. This work was supported by the Ministry of Science and Technology under Grant 108-2221-E-007-106-MY3 and Grant 109-2221-E-007-095-MY3. *(Corresponding authors: Wan-Lun Tsai; Min-Chun Hu.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Research Ethics Committee of National Tsing Hua University under Application No. 10810HE096, and performed in line with the Human Subjects Research Act Declared by the Ministry of Health and Welfare, Taiwan.

Wan-Lun Tsai and Li-Wen Su are with the Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan 701, Taiwan (e-mail: lookoutking@gmail.com; susan31213@gmail.com).

Tsai-Yen Ko was with the Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan 701, Taiwan. She is now with Carnegie Mellon University, Pittsburgh, PA 15219 USA (e-mail: kr.tzy@gmail.com).

Tse-Yu Pan and Min-Chun Hu are with the Department of Computer Science, National Tsing Hua University, Hsinchu 300, Taiwan (e-mail: typan@mx.nthu.edu.tw; anitahu@cs.nthu.edu.tw).

Digital Object Identifier 10.1109/TLT.2022.3145093

Due to the technical demands in basketball, both physical and mental preparations play an important role in the performance of the players [4]. Physical ability training helps the players run faster and jump higher, and mental ability training helps the players become capable of attacking or defending more efficiently. This article focuses on the aspect of perceptual training related to making precise offensive decisions. The abilities to read the defense (i.e., analyze the position and strategy of the opponent in mind) and react precisely as quickly as possible are necessary skills to become proficient as an offensive player. For example, if the defender is within an arm's length away from another player, the player should not shoot the ball, but rather should quickly cut across or pass the ball to a wide-open teammate. Unfortunately, even for a professional player, it is not easy to make perfect attack decisions precisely at the right time in a highly competitive basketball game. As the saying goes, "practice makes perfect," so excellent decision-making is the result of years of practicing and training. Using VR, athletes are able to be trained in a well-controlled condition that mimics the real-world competition [5]. Repeatable scenarios in VR can also provide an athlete with unlimited opportunities to practice.

Since making the right decisions plays an important role in a sports competition, many studies [6]–[8] have investigated approaches and attempts to determining the crucial decision-making factors that most highly influence the effectiveness of training. Arias-Estero *et al.* [7] organized a tournament to analyze decision-making abilities of young basketball players. They stated that although young players need a lot of practice to improve their decision-making skills, there are few opportunities to obtain successful practice during the game. Raab *et al.* [8] emphasized that successful performance in sports is the combination of deciding the type of movement and the process to perform it perfectly. It was concluded that a mixture of decision and behavioral training is advisable. That is, the athletes should learn what decision they should make and what physical action they should perform at the same time.

As mentioned above, perception and action abilities are both important skills an athlete should have. In addition, perception–action training has been proven to be beneficial to athletes during training programs. In this article, an action-aware VR-based basketball offensive decision-making framework is proposed to improve the decision-making ability of athletes. The proposed interactive system consists of a sensor-based action recognition framework and virtual defensive scenarios displayed via the VR head-mounted display (HMD), as shown in Fig. 1. During the training, the trainees should

Fig. 1. User is trained in the proposed system with a 360° video.

perform proper offensive actions when facing different defensive conditions. If the trainee makes an improper decision or action, the system provides suggestions to guide the trainee. Benefited from the artificial intelligence (AI)-based action recognition method, our system enables athletes to do perception–action training by themselves. Furthermore, we conducted a feasibility study to investigate the effectiveness of the proposed framework in both subjective and objective manners.

The contributions of this article are summarized as follows.

1) An action-aware basketball offensive decision-making training system is proposed to provide perception–action training for athletes. The proposed system provides real-time feedback based on the AI-based action recognition model, which enables interactive self-training for novice players. To train the action recognition model, we collected an inertial measurement unit (IMU)-based basketball action dataset, which contains 11 kinds of actions. To the best of our knowledge, it is the first IMU dataset recorded for basketball action recognition, and we will release it to the research community.
2) A feasibility study on the effectiveness and technology acceptance of the proposed framework is designed and conducted. The results show that compared with the conventional training method, our proposed system improves the decision-making ability of players in terms of the reduction in the decision time. According to the questionnaire results, participants showed high intention to use our proposed framework.
3) A comparison between various virtual content (i.e., prerecorded 360° video and 3-D virtual content generated by a computer) is conducted. The cost of prerecording 360° training videos is much higher in terms of both time and human labor. We suggested using 3-D computer-simulated content to improve the decision-making ability in sports because the differences in training effectiveness and presence between both kinds of content are not significant in the experimental result.

II. Related Work

Currently, multimedia technology is commonly used in the training of the perceptual—cognitive skills required to play sports. Some studies [9]–[13] exploited video-based training to improve the players' ability to make decisions and also evaluated their reaction time in specific situations, such as measuring the time during which a kick or punch occurred for a karate athlete in a defensive position. These papers focused on the evaluation of decision-making using video-based training in specific sports conditions.

Hohmann *et al.* [10] conducted an experiment on the effectiveness of 2-D and 3-D decision training in youth handball teams using video content. They attempted to evaluate the decision time after the participants were trained using 2-D and 3-D video approaches as well as the quality of such approaches. Their report showed that 3-D video training is more useful for reducing decision time, but does not affect decision quality. Increasing importance has been attached to sports vision training (SVT) in recent years. Appelbaum and Erickson [1] broadly reviewed dozens of digital-based SVT approaches, such as visual-motor reaction devices, NeuroTracker [14], and VR platforms [15].

Many studies [16]–[19] have discussed the possibility of using virtual environments to assist with sport training. Targeting handball goalkeeper training, Vignais *et al.* [17] investigated the visual perception preference trainees for video clips and virtual environments. They found that goalkeepers performed more effectively and more accurately when virtual environment content was used during training. Craig [18] explored the feasibility of using VR to determine how perceptual-based information guides decisions in sports, such as the judgment related to making a curved free kick in soccer and the decision to engage in deceptive movements in rugby. Since VR technology was not yet refined, and the devices were still very expensive, people tended to simply use video playback in sports training before 2014. Although the integration of movement information and simulated environment was not general in sports-related contexts, they anticipated the future of utilizing VR to enhance athlete performance when VR technology became more accessible to everyone.

Currently, VR technology has become much more popular, and the development of the VR HMD has led to a trend of using 360° videos in sports-specific training. StriVR Labs [20] and Eon Sports [21] provide prerecorded panorama videos to replicate a real-world scenario in baseball, football, skiing, and hockey. Wearing an HMD, an athlete can repeatedly immerse in these 360° videos from a particular perspective. Isogawa *et al.* [22] investigated the effectiveness of the utilization of VR in baseball batter training. They evaluated the decision and reaction times of a batter in four various training environments: 1) a real environment; 2) a flat 2-D video; 3) a 360° video; and 4) a reproduced virtual space. The result showed that panoramic views may be able to provide realistic scenarios in terms of timing control. Ross-Stewart *et al.* [3] conducted an imagery-assisted VR training program to increase mental skills of an NCAA Division I baseball team. From the feedback of assistant coaches in the team, the program helped players visualize the mechanical adjustments to their swing.

Instead of using 360° videos, some researchers [15], [23]–[25] reconstructed virtual training spaces using computer simulations to mimic real-world training environments for football, basketball, and karate. Neumann *et al.* [26] gave a comprehensive review of endurance sports, such as running and cycling. They developed a conceptual model that considers many

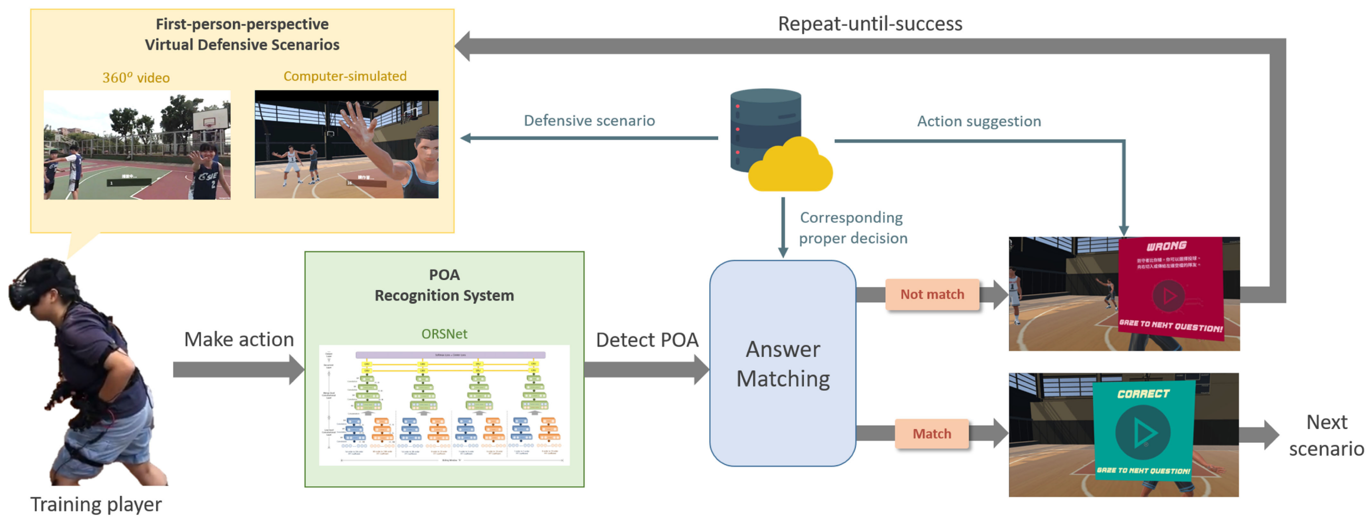


Fig. 2. User wearing motion capture with 16 IMU sensors experiences a 1PP virtual defensive scenario in the HMD and performs a POA correspondingly. The system recognizes the POA performed by the user and presents corresponding feedback to the user via UI according to the similarity between the recognized result and the correct answer prestored in the database.

important factors, and their research also indicated that a VR system with computer-simulated content is a promising assistant in sports training because it provides precise replicable control over the training environment [26].

Both 360° video and computer-simulated virtual spaces can provide users with realistic training experiences, but each one has its own advantages and disadvantages. In terms of the visual experience, a 360° video is captured from a real-life landscape and, therefore, usually makes the user feel more completely involved in the training scene than would be the case in a computer-simulated space. Nevertheless, the mobility and the timing of events are limited to the filmmaker's choice since the video content has to be prerecorded. Computer-simulated virtual space makes it possible for users to walk relatively anywhere in the virtual scene. As for the feasibility, the 360° video must be filmed beforehand, which makes it time consuming to generate comprehensive training scenarios. In contrast, it is more convenient to generate different kinds of controlled training scenario using computer simulations.

In summary, using video-based approaches to assist the training of decision-making ability in sport has been well studied. Some studies have already discussed using VR technology to improve the perceptual skills of athletes. However, an immersive VR-based training framework that considers improving both decision and motor action abilities is still worth exploring. Furthermore, previous works use either prerecorded 360° videos or 3-D computer-simulated content in the VR-based training system. However, the training effectiveness of using various virtual content is not yet well investigated. In this article, we focus on measuring the presence, usability, and knowledge acquisition of perception–action training based on different training media, including a conventional basketball tactics board, 360° video, and 3-D computer-simulated virtual content.

III. Proposed System

As shown in Fig. 2, the proposed basketball VR training system comprises two main components: 1) the first-person-perspective (1PP) virtual defensive scenarios experienced via the HMD (see Section III-A); and 2) a deep-learning-based player offensive action (POA) recognition model (see Section III-B). During the training, the user's movements are captured by an inertial motion capture system and recognized by the model in real time. In addition, the head pose of the user's HMD is used to determine the direction of ball passing. When there is an inappropriate offensive decision made by the user, corresponding action suggestions designed by professional basketball players would be provided. A repeat-until-success mechanism is applied to enable the users to practice in a completely same scenario until they learn the correct decision.

A. *Virtual Defensive Training Scenario*

In the proposed system, the virtual defensive training scenarios are computer-simulated virtual scenes, in which it is easier to customize various detailed settings of defensive scenarios. All the scenarios started from the player in control of the ball. In the virtual training environment, the user will see the defenders and his/her teammates locating at the assigned positions and performing particular behavior, e.g., making cutting movement without basketball, preparing to catch the ball, and setting screen for teammates. For instance, the user might experience a scenario with one match-up defender defending his/her left-side path to the basket. At the same time, the left-side teammate is wide open, and the right-side teammate is under tight defense. In this defensive scenario, the user should cut across to the right side or pass to the wide-open teammate.

To set up the virtual scenarios more conveniently, a training scenario representation file was predefined. The representation file includes positions and the action should perform for each virtual player in the virtual space. Coaches could intuitively build their defensive scenarios by setting the representation files. During the training, the system will automatically transform the information in the file into the 3-D simulated scenario with animated virtual players presenting the defensive scenario.

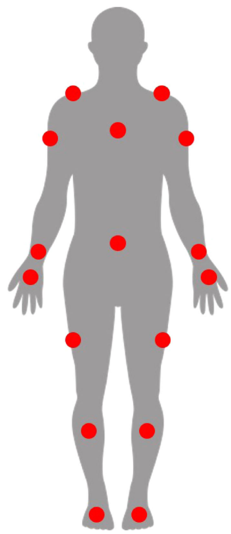


Fig. 3. Placement of the IMU sensors.

B. Basketball Offensive Action Recognition

Vision-based human action recognition methods usually suffer from problems related to occlusion, various lighting, and different camera angles. Therefore, we chose the sensor-based motion capture approach to record the inertial measurements of the body joints and recognize the player action. Based on the captured signals, a hybrid neural network called ORSNet [27] is introduced to do the recognition. In our previous work, we designed ORSNet for the purpose of recognizing basketball official referee signals (ORSs) given the IMU sensor signals captured by the Perceptron Neuron [28] on the human full body. It has been proven to be capable of accurately recognizing 65 types of ORSs, including different scales of gestures. Besides, it is a real-time method that is acceptable for the proposed interactive training system. Note that the Perception Neuron device may be affected by nearby electronics; thus, additional magnetic field should be avoided when using the device.

The recognition system contains 11 common basketball POAs, including shooting with one hand, shooting with two hands, performing a jab step (left and right), showing a shot fake, making a chest pass (left, right, and front), and making an over-the-head pass (left, right, and front). Because these POAs are full-body actions with fewer finger movements, only 16 IMU sensors are used to capture the motion information of the player. The placement of the sensors is shown in Fig. 3. For each IMU, a three-axis accelerometer, as well as a three-axis gyroscope, is used to record the information of body movement. A total of 96 channels of the raw signals are used as the input of the recognition model. Since there is no public dataset of POAs recorded with multiple IMUs, we collected the POA dataset by ourselves to train the recognition model. Fifteen professional basketball players were recruited and asked to perform the 11 types of POAs, and each type of POA was performed ten times. With the collected POA dataset, we used our previous work [27] to train a deep-learning-based recognition model. The output of the model is the probability distribution of the gesture categories. The recognition accuracy on the collected data is 90% based on the leave-one-participant-out-cross-validation evaluation metric.

During the real-time interactive training process, the user wears the sensor-based motion capture suit and performs valid offensive actions to make their decision while watching the defensive scenario in the current training session. To avoid unnecessary calculation, we take the result only when the neighboring predictions demonstrate adequate confidence and calculate the mean of the three sequential output probabilities. A POA is detected only when the mean probability of that POA is higher than 0.7. When a POA is detected and is proper for the current defensive scenario, the system shows a "correct" message on a UI panel, as shown in Fig. 2, and continues the next training session. If the user makes an improper offensive action (e.g., making the jab step when shooting is a better choice), the system shows a "wrong" message and the recommended POA on a UI panel, as shown in Fig. 2.

IV. Experiment

We conducted a between-subject experiment to evaluate the effectiveness of using three different decision-making training scenarios: 1) using a conventional BTB (Group BTB) to convey the key knowledge in specific defending situations; 2) using the proposed system with prerecorded 360° video (Group 360); and 3) using the proposed system with computer-simulated virtual environment (Group CSVE).

A. Participants

Forty-five participants (36 males and nine females) were recruited from a local university campus for this study. They were graduate or undergraduate students ranging in age from 18 to 26 ($M = 21.12$ and SD = 1.89) and were playing on their department basketball team as amateur players. We also assessed the frequency of playing basketball every week ($M = 2.84$ and SD = 1.13), the basketball playing experience ($M = 6.61$ and SD = 3.56), and previous experience with the use of VR. The proportion of the gender in each group was identical (12 males and three females), and all groups had a similar age distribution. In addition, the distribution of playing frequency every week was also similar for each group. Note that the analysis confirmed there to be no significant between-group differences in terms of the demographic variables.

B. Apparatus and Materials

The proposed training system was implemented using the Unity 2017.4.9 game engine and was run on an Intel Core i7-6700K CPU @ 4.00 GHz, with 24-GB RAM and Nvidia GeForce GTX 1080 Ti GPU. The operating system was Windows 10, and HTC Vive Pro was used as the VR display device (two OLED displays, 1080 × 1200 resolution for each display, and 110° field of view). The displaying frame rate was approximately 90 frames/s for both Group 360 and Group CSVE. A Perceptron Neuron suit [28] with 16 IMUs was used to capture the offensive actions performed by each participant. Each IMU consisted of a three-axis accelerometer and a three-axis gyroscope. The sensor data were captured at 60-Hz sampling rate.

The designed training scenarios were discussed and agreed-upon by college basketball coaches. All groups were provided with fair knowledge in the decisions related to basketball offensive actions, including the following:

1) making a shot decision when the defender is more than an arm's length away;
2) using a jab step or cutting movement to make a close defender step back;
3) passing to a teammate who is wide open or cutting to the basket;
4) carefully making a cut decision when your teammate screens for you;
5) using a pump fake to deceive the defender.

There were 19 various defensive scenarios used in the training, including ten basic-level and nine advanced-level decision-making situations. The advanced ones would ask the user to make one more decision after a change in the situation, which was the outcome of making the first decision. Different from making only a single decision at the basic level, the advanced-level situations provided more challenging scenarios requiring players to make consecutive correct decisions. For each defensive scenario, we provided a computer-simulated scene and a corresponding prerecorded 360° video.

The BTB group was taught using a magnetic conventional basketball board combined with colored magnets, which represented offensive players, defensive players, and the ball. As for Group 360, the defensive scenarios were previously captured with a fully spherical 360° VIRB 360 (4K and 30 frames/s) camera [29], which was installed at the same position as the trainees in each scenario. All 19 video scenarios were recorded on the basketball court at the local university campus, and it took approximately 5 h to finish the filming. The same 19 scenarios in the CSVE group were created using the Unity game engine. The reconstructed human skeleton data captured by Perceptron Neuron were also utilized to generate animations of virtual players in different situations.

C. Procedure

Fig. 4 shows the flow of our experiments. We first recruited participants using an online questionnaire. At the beginning of the experiment, the participants were given an introduction to the proposed system and were told that the goal of the experiment was to evaluate the effectiveness of different learning treatments.

The experiment procedure is composed of three main sessions: 1) the pretest session; 2) the learning session; and 3) the post-test session. In the pretest session, participants watched ten panoramic question videos (including five basic levels and five advanced levels) on an LCD display and used a mouse to control the changes in viewing direction in the 1PP video. (Note that in the test, the user watched 360° videos on an LCD display, but the subjects in Group 360 were trained with 360° videos displayed in an HMD.) Each participant was asked to choose one action decision he/she would perform based on the given defensive scenario.

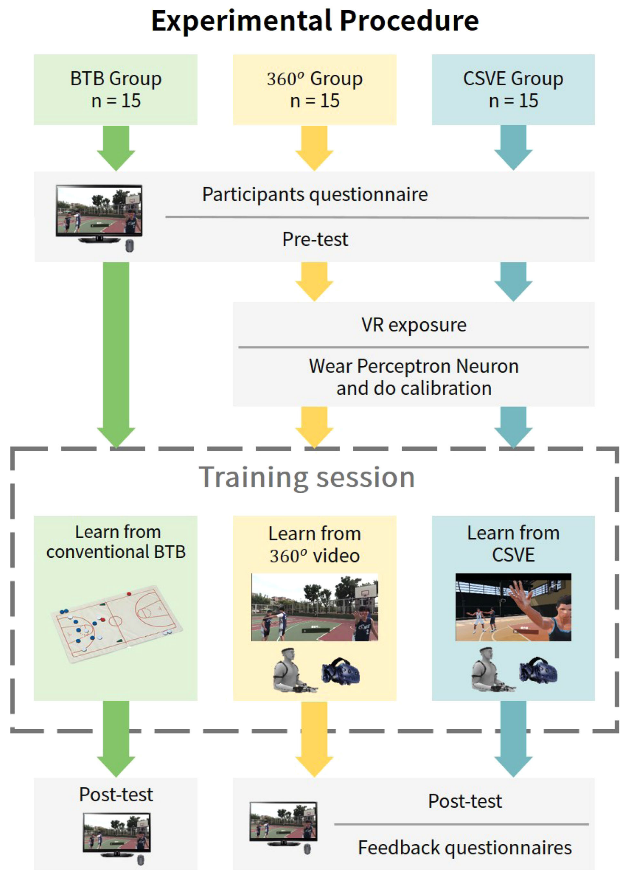


Fig. 4. Experimental procedure for each treatment group.

Next, in the learning session, each group learned about the decision-making skills in each treatment. Subjects in Group BTB learned the main idea of offensive decision from a professional trainer via a conventional BTB. For Group 360 and Group CSVE, the proposed VR system was applied. However, based on a prior study [30], the participants were expected to perform poorly on the first tasks due to being engrossed in the high-fidelity VR. To diminish the effect of this problem, a VR exposure step was applied in our experiment. In the VR exposure step, the participant was asked to play a high-fidelity VR game for 5–10 min before experiencing the VR system. After the VR exposure phase, the motion capture device was attached to the participant, and three calibration poses (including A-pose, T-pose, and S-pose) were performed to acquire the correct sensor data. The experimenter first explained offensive actions that could be recognized by the training system, and then, the training session started.

Finally, in the post-test session, the same test form held as the pretest. Different from the pretest, participants in the 360 and CSVE groups were asked to fill out the presence and usability questionnaires. The total experiment lasted for approximately 40 min for each participant.

D. Measures

In this study, to investigate the feasibility of the proposed perception–action framework, both objective and subjective evaluations were conducted. Objectively, we focused on the improvement of decision-making ability. The score and decision of the pre/post-test tests were used to evaluate participants' abilities in the training. Note that the decision time of the test is the amount of time required to decide a proper POA for each question (the time duration is calculated based on the starting time when the video is played to the participant and the time the participant makes his/her choice).

Subjectively, the perception of the presence and the technology acceptance were assessed. The perception of presence is described as "the feeling of being in an environment." We administered the Slater–Usoh–Steed (SUS) Presence Questionnaire [31] to measure the perception of the presence of Group 360 and Group CSVE and investigated the influence of various virtual content on the feeling of presence. We used the technology acceptance model (TAM) [32] to understand people's acceptance of the proposed training framework. The TAM [32], which is commonly used for assessing the user's adoption of new information technology, was used to analyze the feasibility and usability of the proposed VR training system. Three different aspects of acceptance were considered in the questionnaire: 1) perceived usefulness; 2) perceived ease of use; and 3) behavioral intentions. Perceived usefulness represents that, compared with the conventional physical BTB, the system proposed in this article can provide a better understanding of offensive decision-making in the sport of basketball. Perceived ease of use was defined as how intuitive the participants felt the interaction system to be. Behavioral intention refers to the user's intentions to use the system as an assistant to improve offensive decision-making skills in basketball in the future.

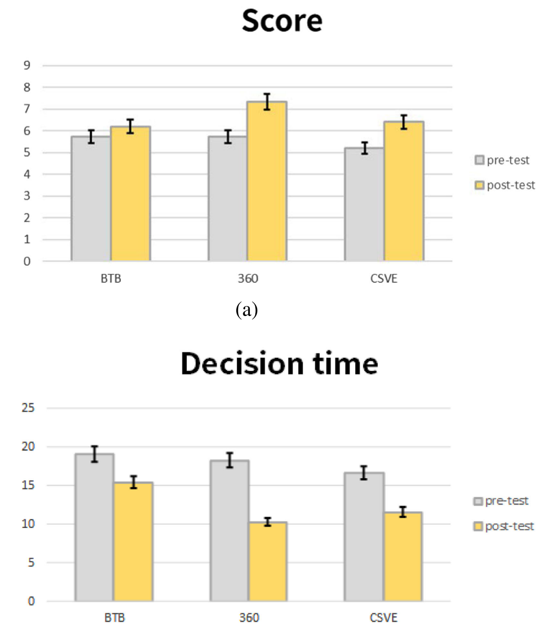
V. Results

A. Objective Evaluation

Fig. 5(a) shows the results for the knowledge acquisition in terms of the test score. In Group BTB, the mean of test scores was 5.73 (SD = 1.38) for the pretest and 6.20 (SD = 1.82) for the post-test. In Group 360, the mean of test scores was 5.73 (SD = 1.27) for the pretest and 7.33 (SD = 1.68) for the post-test. In Group CSVE, the mean of test scores was 5.20 (SD = 1.34) for the pretest and 6.40 (SD = 1.35) for the post-test.

An analysis of covariance (ANCOVA) was conducted to compare the pre/post-test knowledge acquisition in terms of the test score. The independent variables were the three treatment groups. The dependent variable was the post-test score. The pretest score was treated as the covariate to control the initial performance of the participants before they learned. Levene's test of equality of variances showed that the data satisfied the assumption of homogeneity across conditions. There were no statistically significant between-group differences on the pretest knowledge scores in the pairwise comparison.

Fig. 5(b) shows the results for the decision time. In Group BTB, the mean of decision time was 19.08 (SD = 6.11) for the pretest and 15.42 (SD = 5.14) for the post-test. In Group 360,



(a)

(b)

Fig. 5. Histogram results of the measurements. (a) Histogram of the means and standard deviations for the knowledge acquisition scores required for each treatment group. (b) Histogram of the means and standard deviations for the decision time required for each treatment group.

the mean of decision time was 18.23 (SD = 7.53) for the pre-test and 10.30 (SD = 2.26) for the post-test. In Group CSVE, the mean of decision time was 16.65 (SD = 4.21) for the pre-test and 11.58 (SD = 2.14) for the post-test.

An ANCOVA was conducted to compare the pre/post-test amount of decision time. The independent variables were the three treatment groups. The dependent variable was the post-test decision time. The pretest decision time was treated as the covariate to control the initial performance of the participants before they learned. The homogeneity of variance was proven across conditions using Levene's test of equality of variances. There was a main effect on the decision time of post-test results ($F(2, 38) = 10.403, p < 0.001$). Further pairwise analysis showed that Group 360 had a statistically significantly higher value than Group BTB ($p < 0.001$), and also, Group CSVE had a statistically higher value than Group BTB ($p < 0.01$).

B. Subjective Evaluation

We followed the work in [31] to calculate two kinds of score of the SUS questionnaire, which are SUS mean and count. The SUS count was calculated as the number of questions obtaining a score of 6 or 7 among all six questions. Thus, if a participant's answers were 5, 6, 7, 5, 6, and 5, he/she would have an SUS count of 3. The results of these measurements for the Group 360 and Group CSVE are reported in Table I. The Cronbach's alpha values for the presence ratings in the Group 360 and Group CSVE were 0.916 and 0.848, respectively. An independent t-test on these measurements was conducted. There were no significant between-group differences for Group 360 and

TABLE I
MEANS AND STANDARD DEVIATIONS OF THE SUS SCORE AND COUNT FOR GROUP 360 AND GROUP CSVE

Group	SUS Count	SUS Mean
360	3.33 ± 2.18	5.59 ± 1.00
CSVE	3.06 ± 1.94	5.36 ± 1.00

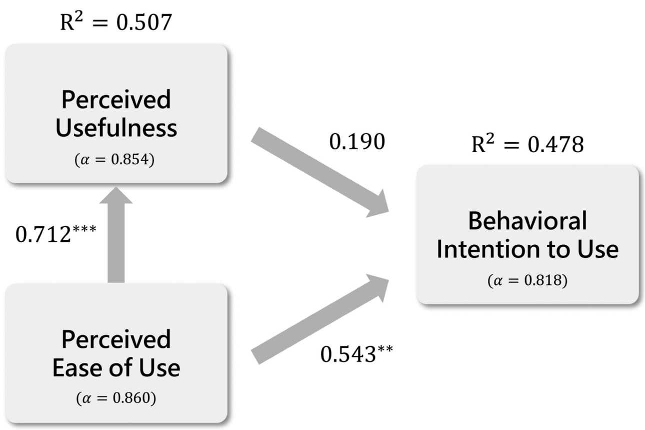


Fig. 6. Regression analysis of each aspect of the TAM.

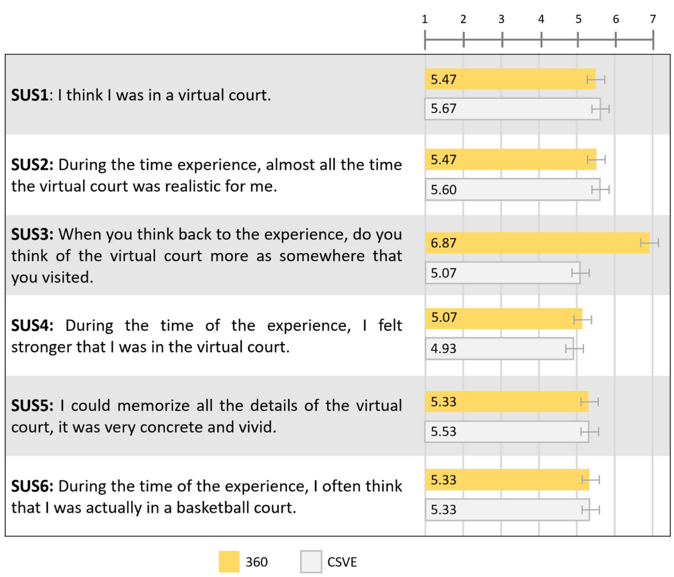


Fig. 7. Means and 95% confidence for the individual question in the SUS score of Group 360 and Group CSVE.

Group CSVE in either of the presence scores. The content and the mean of each question are reported in Fig. 7.

The content and mean of each question of the TAM are shown in Fig. 8. The Cronbach's alpha for each aspect of the TAM was 0.854, 0.860, and 0.818, respectively. All the Cronbach's alpha coefficients were considered acceptable. The means of each aspect of acceptance were 4.59 (SD = 1.01), 5.13 (SD = 1.06), and 5.92 (SD = 0.89), respectively. A Pearson's correlation was applied to measure the correlations between each aspect of acceptance. The matrix results are shown in Table II. In addition, we used a regression analysis (see Fig. 6) to determine the relationships between them. The results indicated that perceived usefulness was not a significant

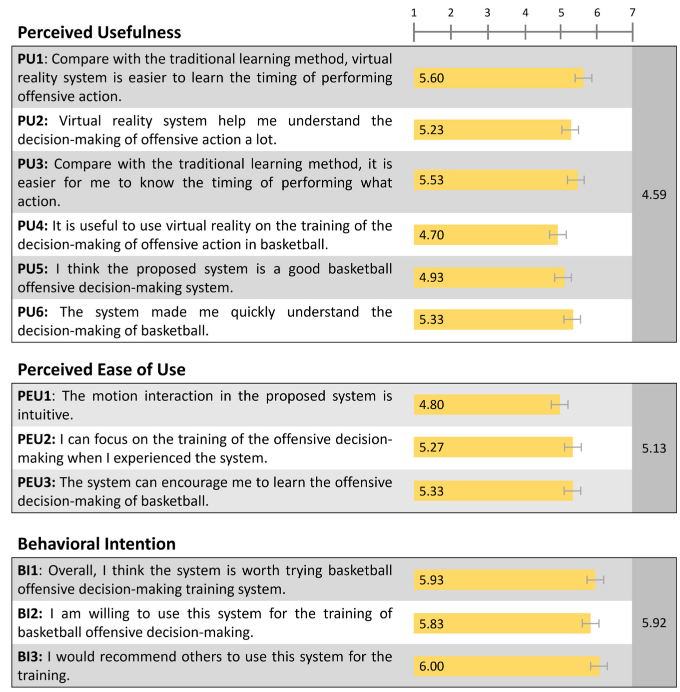


Fig. 8. Means and 95% confidence for the individual question in the usability questionnaire.

TABLE II
CORRELATION MATRIX OF EACH ASPECT OF ACCEPTANCE IN THE USABILITY QUESTIONNAIRE

Construct	PE	PEOU	BI
PE	1.000		
PEOU	0.712^{***}	1.000	
BI	0.577^{**}	0.679^{***}	1.000

$^{***}p<0.01$, $^{**}p<0.05$

predictor of behavioral intention. On the other hand, perceived ease of use significantly affected perceived usefulness.

C. Discussion

The results showed that there were no statistically significant differences in the knowledge score results in the pairwise comparison. To make the questions in the knowledge test more concrete for the participants, 360° panorama videos were used as the content. Participants answered the panoramic-based knowledge test on an LCD display. The resemblance of the content made it inevitable that Group 360 could achieve the best performance on the post-test score (360: $M = 7.33$, CSVE: $M = 6.40$, and BTB: $M = 6.20$) and knowledge acquisition (360: $M = 1.60$, CSVE: $M = 1.20$, and BTB: $M = 0.47$). However, in terms of decision time, both VR training groups exhibited a significant improvement in reducing the time required to make action decision compared to Group BTB. The result was similar to that reported in [10], which demonstrated that the training using higher display fidelity may benefit the performance of the player in terms of the reduction of decision time rather than the decision accurateness. A player can make an early decision suffering from an incorrect decision. In addition, the timing required to performing an action is important in many fast-paced sports.

An improvement in reaction time can help a player find better opportunities in advance. Nonetheless, more defensive scenarios and retention-testing should be used to further evaluate small improvements in decision quality.

The investigation on using different types of virtual content showed that there were no statistical differences between using 360° video and a computer-simulated virtual environment in terms of the knowledge score, reductions in decision time, and self-reported presence (360: M = 5.59, SUS-COUNT: M = 3.33 and CSVE: M = 5.36, SUS-COUNT: M = 3.07). Considering the individual answer in the presence questionnaire, there was a small gap in the mean score on Q3 between the two kinds of media. Question 3 was: "When you think back to the experience, do you think of the virtual court more as somewhere that you have visited?" Since the 360° videos were captured on a local campus basketball court, all the participants in Group 360 (who are local students) felt familiar with the virtual content. Hence, most of the participants rated Q3 as "7. Strongly agree," which, consequently, made the mean score extremely high (M = 6.9 and SD = 0.3).

In Section II, both the pros and cons of the 360° video and computer-simulated virtual environment were stated. A 360° video can provide visually excellent real-life experiences, and computer-simulated virtual environments make designing detailed scenarios more feasible. To film stable viewing panoramic videos that provide a better experience, we installed the 360° camera in a fixed position. Since the camera view was not changed with the user when he/she performed a cut or jab step, we found that some participants felt confused during the 360°-video-based training. Without the oral hints given by the experimenter, they were disoriented because the first-person view did not follow their own body movements. In the evaluation results in Section V, the effect of using different types of virtual content on the training of decision-making is small. It took 5 h to capture 19 defensive scenarios, which covered only a part of complex on-court situations. The postprocessing required for producing precise training videos is also time consuming. In contrast, a computer-simulated virtual environment approaches would be suggested to use, since it can generate controllable comprehensive training scenarios in a more effective way.

Every aspect of acceptance in the usability questionnaire, including perceived usefulness (M = 4.59 and SD = 1.01), perceived ease of use (M = 5.13 and SD = 1.01), and behavioral intentions (M = 5.92 and SD = 0.89), was rated over four points on average. The score for perceived usefulness, indicating the usability of the proposed system, was relatively lower than the other two areas, and the regression analysis also indicated that perceived usefulness has no significant effect on behavioral intention. However, the participants still showed high intention to use the VR system in their real-life training.

VI. Conclusion

The results showed that knowledge acquisition has no significant difference between the conventional approach and the VR-based method. However, the improvement in the decision time was evident. Participants who used the proposed action-aware VR-based system in training could decide faster than those learned in conceptual teaching, which demonstrated the possibility of introducing this system to enhance athletes' decision-making in the training.

Furthermore, there was no obvious difference between using 360° videos and computer-simulated virtual environments in terms of knowledge acquisition, decision time, and level of presence. Considering that producing effective detailed 360° training videos takes time, we would suggest creating more comprehensive defensive virtual scenarios using computer-simulated content to delve into the effectiveness of improving decision quality in sports.

Finally, the proposed system uses the IMU sensor to recognize the action of the trainee and feedback whether the recognized action is a proper decision with respect to the given defensive scenario. Both the quality of the recorded IMU signals and the accuracy of the proposed AI action recognition model would affect the learning effectiveness. Users should notice the effect of additional magnetic fields when using the Perception Neuron. Owing to the high complexity of offensive actions in the sport of basketball, we will strengthen the recognition model by improving the accuracy and adding more action types, such as one-handed passing. An individual player's offensive aggressiveness and actions are important factors related to successful execution of a tactic. In addition, being familiar with a tactic composed of specific player routes is also important. In the future, we will integrate the proposed action-aware VR training system with a tactical route learning system to provide a more comprehensive and realistic training scenario.

References

[1] L. G. Appelbaum and G. Erickson, "Sports vision training: A review of the state-of-the-art in digital training techniques," *Int. Rev. Sport Exercise Psychol.*, vol. 11, no. 1, pp. 160–189, 2018, doi: 10.1080/1750984X.2016.1266376.

[2] M. Wellner, R. Sigrist, J. von Zitzewitz, P. Wolf, and R. Riener, "Does a virtual audience influence rowing?," *Proc. Inst. Mech. Eng. P, J. Sports Eng. Technol.*, vol. 224, no. 1, pp. 117–128, Mar. 2010, doi: 10.1243/17543371JSET33.

[3] L. Ross-Stewart, J. Price, D. Jackson, and C. Hawkins, "A preliminary investigation into the use of an imagery assisted virtual reality intervention in sport," *J. Sports Sci.*, vol. 6, no. 1, pp. 20–30, 2018, doi: 10.17265/2332-7839/2018.01.003.

[4] A. Gaggioli, L. Morganti, M. Mondoni, and A. Antonietti, "Benefits of combined mental and physical training in learning a complex motor skill in basketball," *Psychology*, vol. 4, no. 9, pp. 1–6, Sep. 2013, doi: 10.4236/psych.2013.49A2001.

[5] P. Düking, H.-C. Holmberg, and B. Sperlich, "The potential usefulness of virtual reality systems for athletes: A short SWOT analysis," *Front. Physiol.*, vol. 9, p. 128, Mar. 2018, doi: 10.3389/fphys.2018.00128.

[6] B. L. Smits, G.-J. Pepping, and F. J. Hettinga, "Pacing and decision making in sport and exercise: The roles of perception and action in the regulation of exercise intensity," *Sports Med.*, vol. 44, no. 6, pp. 763–775, Apr. 2014, doi: 10.1007/s40279-014-0163-0.

[7] J. L. Arias-Estero, F. M. Argudo, and J. I. Alonso, "One-on-one situation decision-making according to equipment in youth basketball," *Int. J. Sports Sci. Coaching*, vol. 13, no. 1, pp. 72–77, Feb. 2018, doi: 10.1177/1747954117746494.

[8] M. Raab, R. S. Masters, and J. P. Maxwell, "Improving the 'how' and 'what' decisions of elite table tennis players," *Hum. Movement Sci.*, vol. 24, no. 3, pp. 326–344, Jun. 2005, doi: 10.1016/j.humov.2005.06.004.

[9] M. Mudric, I. Cuk, A. Nedeljkovic, S. Jovanovic, and S. Jaric, "Evaluation of video-based method for the measurement of reaction time in specific sport situation," *Int. J. Perform. Anal. Sport*, vol. 15, no. 3, pp. 1077–1089, Dec. 2015, doi: 10.1080/24748668.2015.11868852.

[10] T. Hohmann, H. Obelöer, N. Schlapkohl, and M. Raab, “Does training with 3D videos improve decision-making in team invasion sports?,” *J. Sports Sci.*, vol. 34, no. 8, pp. 746–755, Jul. 2016, doi: 10.1080/02640414.2015.1069380.

[11] P. Larkin, C. Mesagno, J. Berry, M. Spittle, and J. Harvey, “Video-based training to improve perceptual-cognitive decision-making performance of australian football umpires,” *J. Sports Sci.*, vol. 36, no. 3, pp. 239–246, Mar. 2018, doi: 10.1080/02640414.2017.1298827.

[12] P. Larkin, C. Mesagno, M. Spittle, and J. Berry, “An evaluation of video-based training programs for perceptual-cognitive skill development. A systematic review of current sport-based knowledge,” *Int. J. Sport Psychol.*, vol. 46, no. 6, pp. 555–586, Nov./Dec. 2015, doi: 10.7352/IJSP.2015.46.555.

[13] M. Lorains, K. Ball, and C. MacMahon, “An above real time training intervention for sport decision making,” *Psychol. Sport Exercise*, vol. 14, no. 5, pp. 670–674, Sep. 2013, doi: 10.1016/j.psychsport.2013.05.005.

[14] NeuroTracker, “Neurotracker,” 2018. Accessed: Jan. 29, 2020. [Online]. Available: https://neurotracker.net/

[15] Y. Huang, L. Churches, and B. Reilly, “A case study on virtual reality American football training,” in *Proc. Virtual Reality Int. Conf.*, 2015, pp. 1–5, doi: 10.1145/2806173.2806178.

[16] A. E. Voyskunskiy, A. M. Chernorizov, G. Y. Menshikova, and Y. P. Zinchenko, “Technologies of virtual reality in psychology of sport of great advance: Theory, practice and perspectives,” *Psychol. Russia, State Art*, vol. 4, no. 1, pp. 129–154, 2011, doi: 10.11621/pir.2011.0008.

[17] N. Vignais, R. Kulpa, S. Brault, D. Presse, and B. Bideau, “Which technology to investigate visual perception in sport: Video vs. virtual reality,” *Hum. Movement Sci.*, vol. 39, pp. 12–26, Feb. 2015, doi: 10.1016/j.humov.2014.10.006.

[18] C. Craig, “Understanding perception and action in sport: How can virtual reality technology help?,” *Sports Technol.*, vol. 6, no. 4, pp. 161–169, Oct. 2013, doi: 10.1080/19346182.2013.855224.

[19] S. T. Cotterill, “Virtual reality and sport psychology: Implications for applied practice,” *Case Stud. Sport Exercise Psychol.*, vol. 2, no. 1, pp. 21–22, 2018, doi: 10.1123/cssep.2018-0002.

[20] *Strivr—Immersive Training Solutions*, Strivr Labs, Inc., Menlo Park, CA, USA, 2016. Accessed: Jan. 29, 2020. [Online]. Available: http://www.strivrlabs.com/

[21] *Eon Sports VR*, Eon Sports, 2016. Accessed: Jan. 29, 2020. [Online]. Available: https://eonsportsvr.com/

[22] M. Isogawa *et al.*, “What can VR systems tell sports players? Reaction-based analysis of baseball batters in virtual and real worlds,” in *Proc. IEEE Conf. Virtual Reality 3D User Interfaces*, Mar. 2018, pp. 587–588, doi: 10.1109/VR.2018.8446073.

[23] A. Covaci, C.-C. Postelnicu, A. N. Panfir, and D. Talaba, “A virtual reality simulator for basketball free-throw skills development,” in *Technological Innovation for Value Creation*. Berlin, Germany: Springer, Feb. 2012, pp. 105–112.

[24] Y. S. Pai, M. Isogai, K. Kunze, T. Nakao, and H. Kimata, “UbiTrain: Leveraging the physical and virtual environment for ubiquitous sports training,” in *Proc. ACM Int. Joint Conf. Int. Symp. Pervasive Ubiquitous Comput. Wearable Comput.*, 2018, pp. 202–206, doi: 10.1145/3267305.3267646.

[25] N. Vignais, B. Bideau, C. Craig, S. Brault, F. Multon, and R. Kulpa, “Virtual environments for sport analysis: Perception-action coupling in handball goalkeeping,” *Int. J. Virtual Reality*, vol. 8, no. 4, pp. 43–48, Jan. 2009, doi: 10.20870/IJVR.2009.8.4.2748.

[26] D. L. Neumann *et al.*, “A systematic review of the application of interactive virtual reality to sport,” *Virtual Reality*, vol. 22, no. 3, pp. 183–198, Sep. 2018, doi: 10.1007/s10055-017-0320-5.

[27] T.-Y. Pan, C.-Y. Chang, W.-L. Tsai, and M.-C. Hu, “ORSNet: A hybrid neural network for official sports referee signal recognition,” in *Proc. 1st Int. Workshop Multimedia Content Anal. Sports*, Oct. 2018, pp. 51–58, doi: 10.1145/3265845.3265849.

[28] N. Ltd., “Perceptron Neuron,” 2018. Accessed: Jan. 29, 2020. [Online]. Available: https://neuronmocap.com

[29] G. Ltd., “Virb 360,” 2018. Accessed: Jan. 29, 2020. [Online]. Available: https://www.garmin.com.tw/products/intosports/virb-360/

[30] R. P. McMahan, D. A. Bowman, D. J. Zielinski, and R. B. Brady, “Evaluating display fidelity and interaction fidelity in a virtual reality game,” *IEEE Trans. Vis. Comput. Graph.*, vol. 18, no. 4, pp. 626–633, Apr. 2012, doi: 10.1109/TVCG.2012.43.

[31] M. Usoh, E. Catena, S. Arman, and M. Slater, “Using presence questionnaires in reality,” *Presence, Teleoperators Virtual Environ.*, vol. 9, no. 5, pp. 497–503, Oct. 2000, doi: 10.1162/105474600566989.

[32] F. D. Davis, “User acceptance of information technology: System characteristics, user perceptions and behavioral impacts,” *Int. J. Man- Mach. Stud.*, vol. 38, no. 3, pp. 475–487, Mar. 1993, doi: 10.1006/imms.1993.1022.

Wan-Lun Tsai received the B.S. and Ph.D. degrees from the Department of Computer Science and Engineering, National Cheng Kung University, Tainan, Taiwan, in 2016 and 2021, respectively.

Her research interests include computer graphics, virtual reality, and human–computer interaction.

Li-Wen Su received the B.S. degree from the Department of Computer Science and Information Engineering, National Cheng Kung University (NCKU), Tainan, Taiwan, in 2019, and the M.S degree from the Department of Computer Science and Information Engineering, National Taiwan University, Taipei, Taiwan, in 2021.

She is currently with the Department of Computer Science and Information Engineering, NCKU.

Her research interests include human–computer interaction and virtual reality.

Tsai-Yen Ko received the B.S. degree from the Department of Computer Science and Engineering, National Cheng Kung University, Tainan, Taiwan, in 2019. She is currently working toward the master’s degree in entertainment technology with Carnegie Mellon University, Pittsburgh, PA, USA.

Her research interests include human–computer interaction, user experience, virtual reality, and augmented reality.

Tse-Yu Pan (Member, IEEE) received the B.S. degree from the National Taiwan University of Science and Technology, Taipei, Taiwan, in 2013, and the Ph.D. degree from National Cheng Kung University, Tainan, Taiwan, in 2018, both in computer science and information engineering.

He is currently a Postdoctoral Researcher with National Tsing Hua University, Hsinchu, Taiwan.

His research interests include human–computer interaction, digital signal processing, pattern recognition, computer vision, and multimedia information systems.

Dr. Pan was the recipient of the Doctoral Fellowship from the Pan Wen Yuan Foundation in 2016, the Student Travel Grant of Multimedia Conference from the ACM Special Interest Group on Multimedia in 2017, and the Excellent Reviewer Award at 2018 IEEE Visual Communications and Image Processing. He is a Member of Phi Tau Phi.

Min-Chun Hu (Member, IEEE) received the B.S. and M.S. degrees in computer science and information engineering from National Chiao Tung University, Hsinchu, Taiwan, in 2004 and 2006, respectively, and the Ph.D. degree in Department of Computer Science and Engineering from the Graduate Institute of Networking and Multimedia, National Taiwan University, Taipei, Taiwan, in 2011.

She is currently an Associate Professor with the Department of Computer Science, National Tsing Hua University, Hsinchu.

From 2012 to 2017, she was an Assistant Professor with the Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan, Taiwan, where she became an Associate Professor in 2018. She has authored or coauthored more than 90 papers in international journals and conferences. Her research interests include digital signal processing, multimedia content analysis, machine learning, computer vision, computer graphics, virtual reality, and augmented reality.

Dr. Hu was the recipient of the Exploration Research Award from the Pan Wen Yuan Foundation in 2015, the Outstanding Youth Award from the Computer Society of the Republic of China in 2017, and the Best Young Professional Member Award of the IEEE Tainan Section in 2018.