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Double-sided Design for Reinforcing Private Training of Basketball with an Advanced Imagery Opponent

Kenji Matsuura *, Hiroki Tanioka *, Stephen Karungaru *,
Tomohito Wada †, Naka Gotoda ‡

Abstract

This study discusses the design issues of the human-computer-interaction environment for developing recognition skills of a basketball player in one-on-one situations. Further, two types of actual implementations are proposed for supporting a slight movement of offense and defense repeatedly. Trainees lack physical opponents when they want to have a one-on-one training session. Thus, this study discusses and designs a software-based opponent for a single trainee who has a limited space in the physical world. Firstly, the system monitors and analyzes the offense player's body movements, providing a counter-movement with the silhouette of a visualized defense whose functions are based on the analysis of the monitored physical movement. The life-sized silhouette is displayed on a large screen in front of the trainee. Secondly, another system provides a realistic offense using a head mount display worn by a defense trainee for defense training. Furthermore, the defense receives feedback after the training. We discussed several findings through the first-round evaluation using these two systems. Finally, the extended function to strengthen the recognizing skill based on the gaze information of defensive players is introduced and evaluated.

Keywords: Mental imagery training, basketball, one-to-one, visualized opponent.

1 Introduction

Feint moves work effectively in several popular team-sports such as volleyball, soccer and basketball. Team sports include various competitions introduced not just by professionals but also by school classes and their clubs because of their commercial value and educational importance. Enthusiastic fans are often excited watching the situation of confrontation which includes the feint by an offense and pursuing by the associated defense. Methods for increasing competitive advantage in team sports can be broadly classified into two categories: team tactics and individual player skills.

* Tokushima University, Japan
† National Institute of Fitness and Sports in KANOYA, Japan
‡ Kagawa University, Japan

In the former, tactical analysis and mathematical modeling based on actual data have been studied using network analysis; players are considered as nodes or field analysis where occupation areas of both teams are compared. For instance, Dectoos et al. proposed a method for detecting used tactics in soccer match data [1], which is a data-driven approach. Further, Perrin et al. [2] proposed an original method of analysis based on the differential equation, which is a dynamical system approach. In both cases, they do not directly treat individual learning of human skills.

Charles et al. [3] described a model that focuses on team-sports and the study is conducted in a field of psychology. They introduced a control system approach for deciding on the next action or reaction where a comparator evaluates the reference value with the input value and then outputs the next human motor action. The reference value in this study indicates the goal value, and the method cannot directly contribute to the relative advantage in a one-on-one situation using feint.

Additionally, though these studies analyze the data or structure of each target sport, they lack the perspective of human learning. Sport psychology studies propose a new paradigm in cognition and learning from a dynamics perspective [4]. Erin et al. discovered the function of the midbrain ventral segmental area in the form of motor learning for brain-machine studies [5]. The study indicates that motor learning takes both internally guided and externally reinforced forms in the complex skill domain. This study focuses on human-learning mechanisms. Our study aims to train a learner in self-regulation mode with the feint condition.

Feint is a deceptive movement used by offense players to trick a defense player. When an offense player encounters a situation, the player considers the movement with a higher possibility of reaching the goal among other options (i.e., making a pass directly to a teammate or moving faster than the opponent toward the goal). The player occasionally makes a feint before the intended movement. The opposing defense player closely monitors the movement of the offense players to avoid being deceived and to ascertain actual motive. However, if the player cannot identify whether or not the opponent is playing a feint move, s/he will follow the expected offense move.

To be successful, the feint must be recognized, judged, planned, and executed in a short period. Such short-time phenomena in sports are studied in [6]; this study considers beach volleyball and states the following: "It is suggested that athletes might implicitly read movement-related patterns in the depicted athlete's body posture. In contrast, novices might use information which is easier to access." This implies that to become skilled in the target sport, players initially (i.e., as beginners) observe characteristic body parts but gradually shift their view to the wider area of an opponent as their mastery of the sport progresses. Thus, beginners must hone their observing skills to understand the broad image of defense. Some studies have addressed the training of players in one-on-one situation using a software system. For example, Kohda et al. proposed a system with sensors and feedback devices associated with a basketball player's movement [7].

Players occasionally face challenging situations, which they, as trainees, cannot receive assistance from humans. Thus, a support system implementing an opponent at each standpoint is necessary for efficient independent training, which assumes inexperienced or novice players as a premise. This study tackles the design of two types of standalone supporting systems for offense and defense players, and also discusses supporting issues for private self-regulated training in a one-on-one situation. In particular, the study for the first stage suggested that the training system for the defense trainee needs supplemental development for reinforcing the recognition ability with gaze awareness functionality. Therefore, we

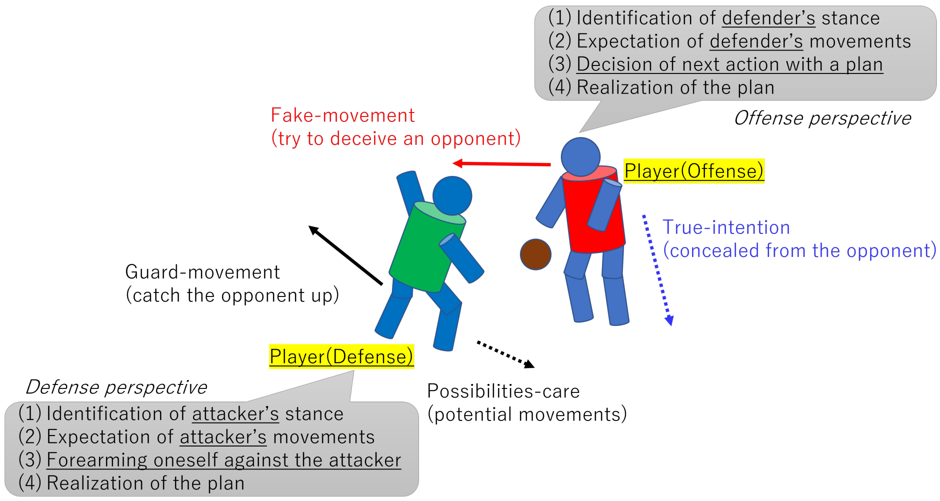

Figure 1: Conceptual illustration of one-on-one situation

have extended the defense training system from the recognition perspective. Furthermore, this study implies to describe the essence of a design based on preliminary discussions and to clarify the effects of a prototype thereof.

2 Private Training Technically Supported by Systems

2.1 Discussion of the effectiveness of a feint

Basketball is one of team sports competing score by putting a ball in the hoop/basket and the game is performed with two teams on a coat. Many people enjoy playing basketball and know what basketball is empirically. However, its complexity makes it hard to learn both team-level and individual level[8]. Though the feint movement is temporarily used in several instances, it is primarily applied by an attacking player. The attacker must learn to observe the defender and move to exploit any openings of the defender. However, defensive players can occasionally challenge a defense-leading feint when they are skillful or experts. Beginners and inexperienced players adopt a passive defensive style where they attempt to follow the attacking player's movement without any active process. Thus, a defense player must know that pursuing determinedly in any way brings relative predominance.

The basic interaction between players standing in mutual confrontation is assumed as follows[9]:

1. An attacking player observes and recognizes the stance of the defense to determine the best movement strategy.
2. An attacking player expects defensive movement when s/he moves in a certain way as initially intended, and several options to move may be available.
3. Among the options considered, an offense player decides which should be performed under current conditions; this may include a feint.
4. An offense player realizes the feint, which was planned and then observes the game and back to the first item.

Figure 1 illustrates both attacking and defensive perspectives. The defensive process is a default counterpart to these items and the main difference is forearming oneself while the offense decides on the next action. Though there are several styles in defense, a passive style of defense is always delayed relative to the recognition of attacking movement without any anticipation. Thus, the feint will succeed when the delay time or the phase difference in a succeeding repetition exceeds a certain range of acceptance. This functions like a closed-loop system in the control-systems field or a dynamical system in nonlinear engineering [10, 11].

2.2 Private training of the offense player

The original scenario for developing motor skills in one-on-one matches consists of four stages, as outlined in [7]. During the practice of the two former stages in this study, a player experiences body movement without a ball when learning. A learner initially trains herself/himself using software defense as a virtual defense before proceeding to the next stage with a real defense, if satisfied. The attacking player can learn these skills in a one-on-one match by concentrating on movement without a ball. The latter two stages have similar processes; however, the learner now practices with a ball allowing them to develop integrated motor skill movements. A previous study [7] focused only on the first stage of the four stages. However, it is necessary to improve the framework even in the focused stage.

Several sensors are used for measuring the acceleration of each body part and a connected computer is used to analyze the measured data. The analytical results are reflected in the defensive movement of an opponent, which is software-based and displayed as a silhouette in a transparent virtual reality (VR) glass worn by the learner. The learner wears acceleration sensors on their waist and legs. According to a previous study[7], the function of the defense is passive and follows the movement of offense with some delay time. Through experimental trials using the system, it has been shown that systems must consider both passive and active styles of defense because real defense techniques show some prediction of the attacking movements in front of the defense.

Defense prediction is modeled using an internally stored analogy model based on the experience and data collected. The requirements from a feasibility viewpoint are that the system works and responses in a short time since getting the input at first. Additionally, the balance of flexibility and precision is crucial, but hard to be dynamically improved as we regard their relationship as a tradeoff.

2.3 Private training of the defense player

This study mainly focuses on attacking players' training. However, defensive player training is also required in addition to offense training because basketball players need both roles in the game, and it is crucial to comprehend the mutual situation through simulated experience.

Thus, additional development is required to present an environment for defense training. Defense learning is easier than offense learning if the supporting system provides a software-based offense; this is because a software-based offense can curtail the process of monitoring the defensive player's reaction without deliberation, making a decision based on its predefined policy or style.

Players in a defense situation need recognition of perceptual inputs of an opponent at first. The players respond to the opponent's recognized movements. In most cases, they do not require strategic judgment regarding the response but require minimum spare time for it. Consequently, the supporting environment for such training is designed in a different style from the main system's implementation.

3 Requirements for the Design of the System

3.1 Fundamental scenario based on theoretical works

The discussion so far implies the importance of different types of supportive environments for one-on-one private training. Consequently, this study independently designs two types of support systems, which include offense and defense to comprehensively train a player. The head mount display (hereinafter, HMD) is used in the project to study the design and development of supporting systems because it can restrain movement in principle. However, the time for wireless communication and processing with a tiny processor should be considered a time-consuming condition for offense trainee. Thus, the current project selects the feedback implementation for the offense trainee on a large screen representing the display image of a high speed computer.

Schmidt's well-known classical theory describes the human schema [12, 13]. Although several research articles have followed the approaches of this theory, three important processes can be defined to systematically support the development of motor skills of humans from a technical viewpoint[14]. These processes are observation, analysis and feedback, which are counterpart processes of the computer side in the human-computer interaction viewpoint.

The first process is a function to monitor the movement of a learner. A basketball player's movement integrates the motor actions of the limbs with those of the body trunk. Several potential body parts can be considered observable targets. Therefore, the monitoring function measures characteristic points to be selected for subsequent counter movement. The next process is an analysis function. When the system obtains data from observation points relevant to human movement, the resulting functions include extraction, conversion and the combination of these data into an abstractive state of the predetermined property. This state can be compared with a stored model as a reference, and its result derives the following direction with the intended feedback. The last process is the implementation of feedback, and there are several means of elaborating the feedback.

The possibilities of the actual design of the support can either be synchronous or asynchronous mode of feedback. Synchronous support provides real-time feedback that must be produced in a short time after receiving the monitored information. However, asynchronous support provides delayed feedback that allows time for deep analysis of data collected during the training. These three processes are also required for implementing the asynchronous style which provides the appropriate feedback information after the training. The basic concept of defense support along with this context is proposed asynchronously. However, to effectively support the offense, real-time feedback can reflect current movements using a just-in-time approach. Subsequent sections mostly describe the supporting environment for offense training which employs a real-time feedback style.

3.2 Observation

When the system detects movement, several possible technologies may be applied to monitor it. An optical motion capture system is a powerful solution for human movements if the movement can be performed in a narrow room. Playing hula-hoop is a typical example [15]. This solution cannot be easily applied to basketball because a relatively wider range of movement is necessary and the infrared radiation reflection markers required to be placed on the body are cumbersome. Another flexible solution is video capturing, in which captured video images are used by image processing techniques for movement analysis [16]. Finally, sensors may be placed on the body directly. However, acceleration sensors are occasionally integrated for monitoring movement. When employing such sensors for training, it is crucial to consider their feasibility and availability.

Compared with these alternative possibilities, capturing video images is the best solution when the system is designed for asynchronous support. Therefore, we used video analysis to create an adaptive prediction model for each learner, and the model was used to analyze the player's movement.

This study also integrates acceleration sensors, which are available for real-time applications in the synchronous support phase for training. Challenging involved with integrating sensors in this context include i) the time condition by which the time lag from monitoring to feedback is severely limited and ii) the fact that the virtual player moves in predefined directions in the active mode. Additionally, acceleration sensors produce observation noise. Thus, noise filtering functions should be implemented.

Hence, the design for supporting offense training has two processed function where predefined prediction models are created in the preparation phase by analysis of captured video contents, and the observed data during training are used to produce real-time feedback. However, the system simply monitors the movement and stores the time series data for post-phase feedback for the defense trainee.

3.3 Analysis

For the offense training system applied in this study, active defense software is used because of the offensive player's current movement. Active defense is defined as having no strategic function, but anticipating how and where the opposing player moves. To work with this expectation, the internal model statistically follows records of previous movements by offensive players. Thus, collecting more than a certain number of video images to create the model is essential. The integration of the statistical model to support motor-learning is proposed via several methodologies such as the Hidden Markov Model (HMM) [17]. However, because feint skills are difficult to monitor in terms of the HMM internal states, this study applies a simple Markov process based on the previously obtained stored data.

For the offense training, such a combined approach is installed. However, for defense training, the system replicates and integrates the trajectory of both the software-based offense movement and the human defense movement to identify the gap in time series. It is a simple method but the system forces a learner to consider the timing of improvement for the next time training.

3.4 Feedback

When describing visual feedback to a learner, two means of implementation are commonly used: direct and indirect images. The former is used to display symbols with stimulating

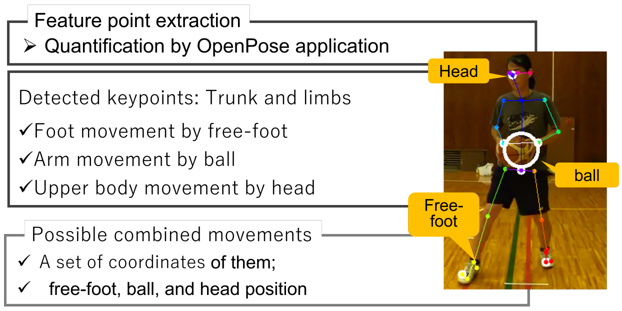

Figure 2: A simplified method of offense movement detection using OpenPose

objects, which instruct the learner for the next action at the appropriate time. The latter is occasionally used to prompt learners to determine the next action and act immediately when the meaning of the feedback is distributed.

These two types of feedback are implemented in a similar interface as in the superimposed method. The defense silhouette is an indirect image for which an artificial object for conveying the message is displayed in front of the silhouette and this is used for offense training. For the defense training, the feedback is implemented in visualized waveforms to demonstrate the gap between the software-based offense and human defense movements. This feedback is performed after the training and the image is displayed on the HMD.

4 Implementation of Offense Training System

4.1 Capturing real offense movement

Data of real human movement are used by the software-based player that controls an attacker to imitate a real player. The OpenPose application, which detects the human body, hand, facial and foot key points for a multi-person system was used to analyze video images of the feint motions of several players [18].

We identified only four characteristic points within the 25 points detected as defaults. These points relate to the limbs and trunk of the body (a free foot, neck, waist, and includes the ball). Feint execution and success depend on a highly nuanced system with six-degrees of freedom, called 3D-6DoF-movements [19, 20]. However, the relationships between body points cannot be easily processed using mathematical methods because of their complexity. Thus, a machine learning library has strong advantages.

Regarding picked-up points, the free foot is detected along with a pivot foot; the detection of a pivot foot is comparatively easy because it moves within a restricted area. Additionally, we used the tool's recommended neck and waist positions. The ball position was assumed based on the detected position of the hands. This process models the ball as a rigid body (Figure 2).

4.2 Process of creating the model from the collected video

The model creation component was used in the previous phase against skill development practice. We used the Python ver.3.8 programming language, which integrated OpenCV library. The resulting model was shown using matplotlib and PyQt5.

Table 1: Conditions of significant movement (ref.[9])

Point	Condition of judging the significant movement
Free-foot	Foot movement speed is out of the range of the threshold value, which is calculated as the pixel size of a ball in each feint situation multiplied by 20 [pixel/s]
Head	Ball speed is out of range of the speed of the free-foot divided by three plus the threshold [pixel/s]
Ball	Same as for head speed

Table 2: Label–index matrix (ref.[9])

Label	Free-foot	Head	Ball
s_0	False	False	False
s_1	False	True	False
s_2	False	False	True
s_3	False	True	True
s_4	True	False	False
s_5	True	True	False
s_6	True	False	True
s_7	True	True	True

The procedure starts by selecting a JSON file provided by OpenPose and using the system to detect the positions of selected points. Subsequently, a median-filter is applied for smoothing and the corrected position is used to detect the speed at each characteristic point. The speed value is applied to determine the feint status label. Position and speed data together with the label assigned are visualized in a graphical window with the video progress of the feint movement as the background.

Threshold values are preset to detect whether or not significant movement occurs. We selected four characteristic points; however, only the data from the waist are related to the head movement because of physical coherence and we use only three points to make the movement label in this study. Table 1 shows the conditions of threshold values.

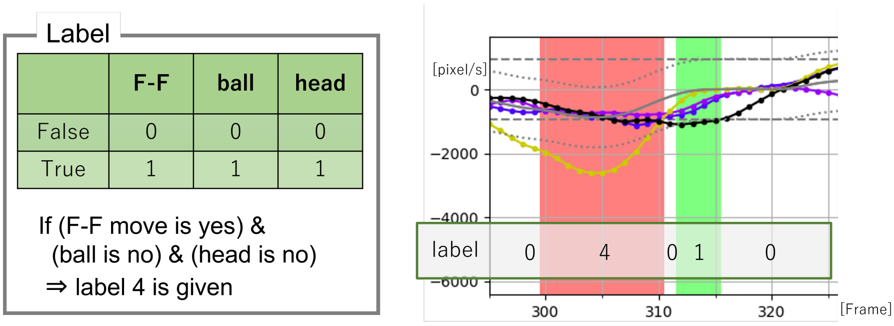

Figure 3: Detected zones and their labels

Table 2 shows label implementation, which applies the conditions of detection for a significant movement described in Table 1. For instance, the free-foot score is out of the range of the predefined condition, which is determined as "True(=1)". If two other points are both "False(=0)", the label index is determined as "s_4" that is derived from (100) which is represented in binary digit format, in this case, indicating that only the free-foot is in motion. Figure 3 shows the zones, which a labeled colored range is applied in either red ("s_4") or green ("s_1") for sample detection. There are several plots with dotted lines in this figure. A pair of dotted lines indicates the bandwidth of thresholds described in Table1. In viewing the zone of label 4, only the yellow line is out of range. The white colored indicates the label of "s_0."

A transition probability matrix, which is output after applying Table 2 is used currently in this study.

$$Q = \{s * | s_0, s_1, s_2, s_3, s_4, s_5, s_6, s_7\} \quad (1)$$

$$A = \{a_{ij} | (freq.of s_i \rightarrow s_j)/(freq.of s_i \rightarrow *)\} \quad (2)$$

We recorded 22 feint trials using four experts as video material. Although this number of recordings was small, each video has been precisely segmented. The model represented in the matrix was then obtained as transition probability.

4.3 Offense training system

We developed a device that integrates an acceleration sensor (LSM9DSI, STMicroelectronics) and a Wi-Fi module to monitor body movements using a micro-computer (ESP32, Espressif Systems). The sensor can be used in various modes; for this study, we used the plus-minus $2g$ range. The device can communicate with the host computer through the Wi-Fi module. The device does not interrupt the learner's movement through wireless communication. The measurement interval was set at $100Hz$.

The system can identify offense movements in this environment and develop the software defense movement for the next action. Although the defense was displayed in transparent VR-glass in the system proposed in [7], this study showed the image as a large screen in front of the offense learner.

Table 3 shows the eight types of silhouette used for the defense. There are seven types of asymmetrical silhouette shapes for the left and right direction, and type 1 in the table is set in the bilateral symmetry. These seven types are available for reverting from left-attention to right-attention. A total of fifteen types of silhouette can be selected automatically according to the posture of an attacking learner.

5 Defense Training System

5.1 Integration of the HMD

The defense training system, which works as an Android application is also designed for learning the responding movement of a defense. An HMD, which has several functionalities such as acceleration sensors in addition to the transparent display are used by a trainee to observe the movement of a defense trainee, and display an artificial offense player on the HMD. The study needs model data of actual offense players that play feint movements to display an artificial offense player. We obtained a specific amount of actual movement

Table 3: Organization of defense silhouette

type	left-arm	right-arm	trunk	left-foot	right-foot
type1	natural	natural	natural	natural	natural
type2	natural	natural	left-tilting	natural	natural
type3	up	natural	natural	natural	natural
type4	up	natural	left-tilting	left	natural
type5	natural	natural	natural	left	natural
type6	natural	natural	left-tilting	left	natural
type7	up	natural	natural	left	natural
type8	up	natural	left-tilting	left	natural

Table 4: Position of the characteristic points of OpenPose

No.	Position	No.	Position	No.	Position
0	Nose	10	RKnee	20	LSmallToe
1	Neck	11	RAnkle	21	LHeel
2	RShoulder	12	LHip	22	RBigToe
3	RElbow	13	LKnee	23	RSmallToe
4	RWrist	14	LAnkle	24	RHeel
5	LShoulder	15	REye	25	Background
6	LElbow	16	LEye		
7	LWrist	17	REar		
8	MidHip	18	LEar		
9	RHip	19	LBigToe		

data for the purpose and the detected data were processed using OpenPose application [21]. Table.4 lists the characteristic points provided by the created model.

5.2 Configuration of a virtual offense

Figure 4 shows the whole process of reproducing offense movements. The monitored movements of actual players include continuous movements of offense players in which they move between left-right directions and a fake of shooting and so forth. Therefore, we segmented the series of data movements and appended several types of label to each segmented data. This procedure was performed manually, and we successfully obtained 45 data which were collected and segmented. The system dynamically picks up several segmented data

Table 5: Level definition of difficulty

Movement element	level 0	level 1	level 2	level3
Left–right movement	On(repeatedly)	On	On	On
Shooting action	Off	Off	On	On
Speed fluctuation	Off	Off	Off	On

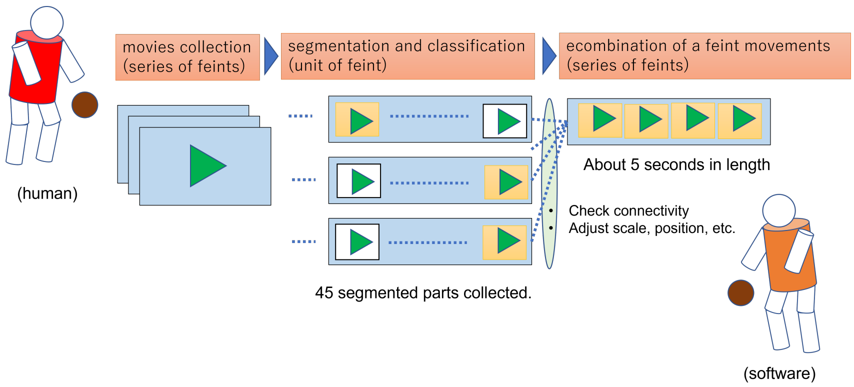

Figure 4: Process of dynamic reproduction of the artificial offense movements

and conjugates them to make an artificial offense plausible. As there were several players involved in creating such data, the system required adjustment of the inter-personal difference in physical characteristics in putting them together and linking. For example, if the standing heights of two players are significantly different, the system must make a contraction or magnification for either sample in concatenation. In another example of conjunction issues, there are certain inconsistencies or discrepancies in movements between leading data and subsequent data where the position of a ball differs from each other. The system automatically compensates for the distance by morphing the process originally developed in such situations.

Table 5 indicates another aspect of providing a virtual offense for defense trainees. What we had in mind for the arrangement function of the difficulty level was implemented and a trainee could select one of the level manually [22]. In the table, the number of levels is set to four with the levels ranging from zero to three; the following three properties were listed; left-right movement, shooting action and speed fluctuation. The highest level is three, where all properties are set to "On". Thus, the system can provide a software-based offense image with unexpected movements.

Using the software-based offense player, a trainee can practice alone by putting on the HMD. This study presents a feedback interface that is displayed after a certain amount of training. The prototype system provides comparative information of movements among the ball, the software offense and the trainee. Further, a waveform presents the phase difference of these three items in the same time series.

6 Trial Use for the First Stage

6.1 Structure of the experiment for supporting offense training

This study tested the designed prototype as a first-stage experiment. In this time especially, we have tested the offense training system. To evaluate differences between active defense newly proposed and passive defense proposed in the past. The active defense was presented as an experimental condition (system A), and the passive defense was presented as the control condition (system B).

The volunteer subjects were sixteen novice players in their twenties (e.g., 20–29). All subjects participated in the experiment for five days. The first day was devoted to accustoming the participants to the system environment. On the first day, they ran five trials with the base system without expectation functions. Thereafter, the participants were divided into groups AtoB and BtoA. The AtoB group used the system in condition A for two days and the system in condition B for the two subsequent days. However, the BtoA group oppositely used the system. The subjects used the system five times each day before answering questionnaires regarding the system used for the day. They also answered a final questionnaire on the last day; they were asked to compare the systems as A and B. Each trial had a maximum time of ten seconds.

6.2 Result of the questionnaire

6.2.1 Active defense

One of the questionnaire items for each trial requested that subjects consider the software defense actively. This question provided five options on the Likert scale. If a learner thought that the defense moved actively, s/he selected either option four or five. Additionally, the final day's questionnaire inquired whether the system was more active on second/third or fourth/fifth days. Comparing the two former days to the latter two days in group AtoB, the average considering the system activity increased in B were two subjects, whereas the corresponding value for A was one. To summarize the 32 answers received, the number of 4/5 answers in condition A was 26 ($sd. = 0.669$) whereas condition B received 25 ($sd. = 0.967$). Condition A exceeded B by only one person, but the $sd.$ score is uneven as the variance of condition B is larger. This result indicates that the activeness of the software defense can be identified to some extent from a subjective viewpoint.

6.2.2 Reality of digitalized defense

Another question is asked about the reality of software defense. If a subject thought that the software defense was more realistic, the subject responded to the question with four/five in the same way as the former question. However, the number of subjects who selected four/five in condition B exceeded that of condition A. The actual score of condition B was 26 ($sd. = 0.898$) whereas that of condition A was 25 ($sd. = 0.780$). As for the reality of the software defense, the passive was more realistic than the active defense based on the judgment of the subjects. We think it is more or less caused by the degree of experience.

6.2.3 Acceleration improvement

We investigated improvements in the degree of acceleration compared with its value on the first day using the maximum acceleration values in each trial. Thus, the maximum acceleration value was observed in condition A with nine subjects; (56 % participants). The mean value of improved acceleration under condition A was 0.015 ($sd. = 0.303$) whereas that of condition B was -0.033 ($sd. = 0.314$).

6.3 Discussion of offense training

The obtained data allow us to discuss future implications. We were unable to distinguish between the two conditions tested because the subjects were only sixteen in total. The response time of the software defense was shorter than that of the non–expectation system.

Additionally, this study's active movement was based on statistical data from previous performances. It should be considered in the future that the result of active defense in the previous section might arise from these reasons. Subjective judgment for active movement of the defense was higher despite such situations.

The subsequent result in reality indicates that the passive defense is a little higher than the proposal. This result is also derived from a subjective questionnaire but did not provide significant impacts for basketball novice learners. We questioned novice subjects in this test, but intend to interview players with more experience in subsequent tests.

The last data for acceleration showed that subject's performance in the proposed condition was highly accelerated compared with the control condition. When the defense acted in the passive mode, a learner of offense moved comparatively slowly because the defense constantly followed the offense movement. However, the active defense does not constantly follow the offense and may account for the observation of maximum acceleration under this condition. We have to make continuous efforts on improving the active behavior of the software.

6.4 Evaluation of a supporting system for defense training

This study tested another environment supporting the learners of defense playing. The procedure used for the trial use was similar to the aforementioned system for offense training. Novice trainees who were voluntary subjects used the system; they were a total of twenty subjects in their twenties.

The structure of this used trial consists of three phases. The pre-phase was used to check the initial status, and to investigate the properties of subjects. The normal system was used five times in this phase. Moreover, we made two homogeneous groups based on the performance of the pre-phase. Both groups A and B used the experimental and the control systems for five times respectively. In addition, they used the normal system five more times to check the performance improvements from the initial status.

We introduced three types of indicators, which were the ratio of tracking performance (TP), the degree of maximum acceleration (MA) and the average reaction time (RT). However, only TP indicated the statistical significance ($p = 0.009 (< .01, n = 20)$ where A($m. = 0.523, sd. = 0.038$) and B($m. = 0.472, sd. = 0.036$)). We assumed that the trainee requires sufficient training time to improve MA and RT relatively. However, the performance in TP was comparatively improved in an easier way than those in MA and RT. In any perspectives, the recognition skill is important.

7 Gaze Awareness to Strengthen the Defense Recognition

7.1 Extended approach for defense trainee

The present study focuses on supporting feint movements learning in private conditions. Trainees, as learners, can train themselves in a self-regulated manner with a supportive environment where they move accordingly in a short time. Through the evaluation, we discovered that some subjects were late in starting the reaction and tardy in moving. They did not quickly recognize the sign of facing an opponent nor the indication to move. Thus, further study needed to reinforce the recognition skill by inducing gaze awareness, which is a well-known approach in computer-supported cooperative work field[23].

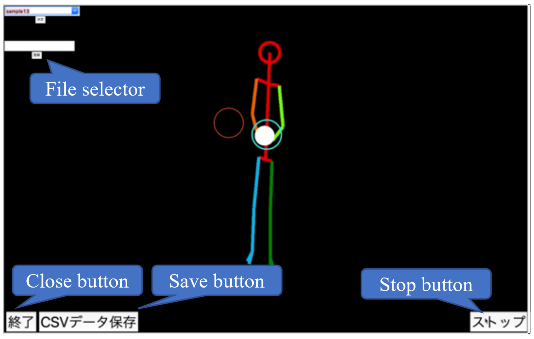

Figure 5: Snapshot of gaze supporting interface (ref.[24])

Figure 5 shows the snapshot of the prototype interface, which supports gaze awareness for the defense trainee[24]. This extension integrates a dynamic time warping (DTW) method for evaluating different length data of time series. A similar approach has already been applied for another condition in developing identification skills for team sports tactics[25]. However, the supporting target is a defense training under one-on-one condition whereas the literature[25] focuses on overlook on two-dimensional simulator of a match.

In this figure, we can find two circles overwrapped on the attacking player model which is dynamically reproduce feints. These circles indicate the gaze information monitored using an eye-tracker device by Tobii cooperation[1]. A circle shows the model view by experienced players monitored previously and reproduced whereas another circle shows the gazing position of a current trainee. We have designed and developed such an interface where the defense trainee can compare the different point of view between her/his eye position and the model eye position of which experienced players have been previously observed. A trainee can distinguish these circles by different color.

The interface does not have the multi-language mode and still have Japanese characters on some buttons. The bottom-left button indicates the closing of the application. Next button to it indicates the save function of the data monitored. The bottom-right button presents the stopping function of the feint of the software offense. The interface has been designed and provided as a prototype while working on it. When the development is completed, we require the estimation of a further proposal of gaze awareness support through the experiment.

7.2 Trial use for the extended stage

7.2.1 Organization and the process

We have conducted further trial use to evaluate the extended system for the defense trainee with gaze awareness environment. The number of voluntary subjects as trainees were 29. They were not experienced subjects of basketball and their age ranged ten's to twenty's.

As we need the model trajectory of experienced user of the system, we ask five experts who are not relevant to actual subjects. They watch the software offense provided by the defense training system described in section 5. We collected twenty-nine data whose length was about ten seconds by five experts and made mean series of coordinates. We use them as the model trajectory of eye movement.

[1] https://www.tobiipro.com/

The procedure of the trial use follows an ordinary style which begins the preliminary investigation to make homogeneous sub-groups. For the preliminary investigation, all subjects watch the software offense of feint movement five times under the same conditions. The DTW score between the model data which is previously generated and the observed data of subjects is calculated respectively. Subjects are divided into three homogeneous groups by statistical procedure. We use Shapiro-Wilk test for normality and each group got p-value at more than $0.60(\geq 0.05)$ respectively. Bartlett's test is also used to test homoscedasticity and got the $p = 0.93(\geq 0.05)$. A p-value of less than $.05(= \alpha)$ was considered statistically significant for both tests. Hence, we regard that we successfully made homogeneous groups. The sub-groups used the different systems for learning as follows;

GroupA, consisting ten members, uses the proposed system described in section7.1 which provides both model trajectory and the observed gaze series of a current subject.

GroupB, consisting ten members, uses the different system which provides only the model trajectory.

GroupC, consisting nine members, uses another different system providing only the subject's gaze coordinates.

All subjects watch seven types of software-based offense with feint movements for three days as learning phase. After the learning phase, they watch the contents which are the same as the preliminary investigation. The system is just monitoring the gaze movements which did not provide any supporting information as in the learning phase.

7.2.2 Result

We compared the monitored gaze data which are DTW score of the model and observed data from statistical viewpoint. Kruskal-Wallis test is performed for analyzing variance on ranks as a non-parametric method at first. As a result, the p-value is $0.048(< .05)$ which means that either one pair of groups has significant difference at least.

Then, we use Steel-Dwass test for multiple comparisons. The p-value between Group A and B is $0.92(\geq .05)$ which means no significance found at this comparison. The p-value between Group A and C is $0.03(< .05)$ which means significant difference found at this comparison. The p-value between Group B and C is $0.23(\geq .05)$ which means no significance found at this comparison.

Only the pair of Group A and C got the significantly difference and we calculated further effect size. Actually *Cliff's* $\Delta = 0.69$ which means comparatively large effects.

We can not get much difference against the GroupB's system. It means that the model view of eye-trajectory is necessary for improvement of the gaze movement. Furthermore, the above result indicates that our approach for reinforcing the recognition by gaze awareness environment induces the positive influence.

8 Conclusion

This study described a double-sided approach by supporting systems for privately training a basketball player. Before applying the system and the environment to users as learners and experts, we have passed the ethical review at the committee of authors' institution. In case we apply the system to not only the conducted experiment but also the actual situation for practice, we have to make the guideline especially for the young students.

Though the existing work designs and implements software-based basketball defense in the passive mode, this study extends it to the active mode to give a human offense as a trainee more reality. We conducted a first trial with sixteen subjects using the prototype. The result did not show a significant difference relative to previous expectations. However, we discovered positive results in subjective viewpoints and performance data.

For defense training on contrary, only tracking performance was significantly improved in five training opportunities. Thus, we will investigate details for other indicators in further experiments. The discussion is touching upon the necessity of gaze awareness interface using an eye-tracking device. Therefore, we have performed the evaluation of the extended system for the defense trainee in terms of recognition reinforcement. The result indicates our proposal gives positive effect for improving how to look the object on the screen.

Further, this study discusses the difference between offense and defense movements from playing and training perspectives. The preliminary discussion made us provide two associated systems for each training. However, we have further room for improving argument where we make efforts on unifying the opposite functions. Thus, one of our concerns of future implications is the methodology of an integrated environment for both trainees which is capable to apply middle level of players. We have to make further efforts on continuing the use and evaluating our environment with employing more players in order to raise the quality of the supporting system.

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Authors' note

This is an extended paper of the conference paper [9]. Authors polished up the context and reorganized the conference paper with new contents as a journal.

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