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Regular Paper

Motion Adaptive Orientation Adjustment of a Virtual Teacher to Support Physical Task Learning

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Abstract: Watching a real teacher in a real environment from a good distance and with a clear viewing angle has a significant effect on learning physical tasks. This applies to physical-task learning in a mixed-reality environment as well. Observing and imitating body motion is important for learning some physical tasks, including spatial collaborative work. When people learn a task with physical objects, they want to try and practice the task with the actual objects. They also want to keep the referential behavior model close to them at all times. Showing the virtual teacher by using mixed-reality technology can create such an environment, and thus has been researched in this study. It is known that a virtual teacher-model's position and orientation influence (a) the number of errors, and (b) the accomplishment time in physical-task learning using mixed-reality environments. This paper proposes an automatic adjustment method governing the virtual teacher's horizontal rotation angle, so that the learner can easily observe important body motions. The method divides the whole task motion into fixed duration segments, and seeks the most important moving part of the body in each segment, and then rotates the virtual teacher to show the most important part to the learner accordingly. To evaluate the method, a generic physical-task learning experiment was conducted. The method was revealed to be effective for motions that gradually reposition the most important moving part, such as in some manufacturing and cooking tasks. This study is therefore considered likely to enhance the transference of physical-task skills.

Keywords: virtual reality, mixed reality, physical task learning, human computer interaction

1. Introduction

The use of Mixed-Reality (MR) technology facilitates stimulating training, in which users can actively explore new ideas and skills without the help of experienced instructors. In addition, trainees are actively involved in the education process, and thus remember more than without the use of MR [5]. Finally, MR use enhances users' perception of, and improves their intuitive interaction with, the real world [1].

Physical-task learning that utilizes virtual reality and/or MR technology has been actively researched. The use of actual equipment in a real environment in physical-task learning is known to be very effective. In light of this, a host of studies have investigated the support of physical-task learning in such an environment by using sensors and virtual reality [15], [17]. The results suggest that MR is suitable for supporting physical-task learning. Thus, we have developed a physical-task learning-support system using MR [8]. The system visualizes a real-world 3D virtual teacher model placed in front of the learner.

Previous research has shown that a virtual teacher-model's position and rotation angle have significant effects on learning [8]. The results show that the virtual teacher's close side-view is the optimal view for physical task learning that involves one-hand motion. However, when the virtual teacher uses both his/her hands, or rotates around, then rotation-angle adjustment becomes necessary.

In this paper, we introduce a novel method of automatically adjusting the virtual teacher-model's rotation angle during run time. The automatic adjustment method is based on the virtual teacher's behavior, more specifically on his/her upper-body movements. The purpose of this method is to ensure that the virtual teacher's most important moved body part in one motion segment is visible to the learner. This is likely to enhance the learning outcome and the learner may feel more comfortable and assured during learning. The outcome was measured in terms of the number of committed errors during a simple physical-task learning experiment.

We chose a simple, generic, push-button physical task as a learning model in this research. This task is considered very simple to perform, because the learner needs only move his/her hand and push one of the buttons. Despite its simplicity, however, the task involves the essential aspects of physical-task learning necessary to prove our hypothesis. To perform such a task, the learner must watch carefully and perform the same actions, in the same exact order, as presented by the virtual teacher. This kind of generic motion can apply to a wide variety of physical tasks, such as using some kinds of musical instruments and machines, performing simple dance movements and sports, building models from sub-models in a predefined order, and constructing new material by mixing sub-materials in a predefined order, etc.

A generic physical-task learning experiment that compares

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the automatic adjustment method with some fixed viewing-angle conditions was conducted to evaluate the method. The experiment results showed that using the automatic adjustment method significantly decreased the number of committed errors.

The remainder of the paper is organized as follows: In Section 2, we discuss related work in greater detail. In Section 3, we present the physical-task learning-support system design specifications. In Section 4, we discuss the automatic adjustment method implementation. In Section 5, we present the conducted experiment specifications. In Section 6, we present the statistical results and the error discussion. Finally, in Section 7, we summarize the paper and discuss future research.

2. Related Work

There have been various studies done on virtual reality and MR-based skill/task learning support, and a number of systems have been developed which employ a virtual teacher to perform the physical task in front of the learner [4], [6], [14], [16], [19]. Some of these systems enhance the learning experience by virtually displaying related information and providing necessary feedback. Such systems have proven useful in various domains, in particular for learning cooking skills, dance skills, sport skills, etc.

Horie et al., for example, proposed an interactive learning system for cooking in an MR environment, using video data extracted from TV cooking programs [7]. The respective videos contain cooking experts performing cooking tasks, and the experts are displayed at a cooking table when needed in a fixed location. Another cooking-navigation system was proposed by Miyawaki et al., and here, a virtual agent that performs actions corresponding to the current cooking step is displayed in a fixed location at a table as well [13].

Regarding dance skills acquisition, Chua et al. proposed a wireless virtual reality system for teaching Chinese ‘Tai Chi’ [4]. The learner’s avatar and the teacher model were rendered in a generated virtual environment, and displayed via a light wireless head-mounted display (HMD). Here, five interaction techniques were tested: one teacher, four surrounding teachers, four side by side, and two superimpositions. All of these techniques were implemented with a fixed teacher’s location and rotation angle. However, the results suggested that the techniques employed had no substantial effect on learning physical tasks. In another study, by Kimura et al., four basic visualization methods were tested in a generic body-movement learning system: face to face, face to face with mirror effects, face to back, and superimposed [9]. The results confirmed that the superimposed method is the most effective for repetition of partial movements, while the others are effective for whole body movements.

In conventional task learning with a real teacher, the teacher observes the learner and intervenes when the learner makes a mistake. To achieve such interactive information feedback for the learner, sensing mechanism of the learner’s behavior is adopted in virtual reality-based learning support systems [14], [15], [17]. Feedback information for the learner is also needed in MR-based task-learning support systems, and capturing the learner’s motion is very important in providing such feedback information [17]. Such motion-capture technology is used in a dancing training system developed by Chan et al. [3]. Here, the virtual teacher is projected on a wall screen, and the learner’s motions are captured and analyzed by the system with feedback provided. To facilitate the observation of moves, the learner can change the demonstration speed and the viewpoint. But, during the practice sessions, the teacher is displaye d into a fixed location, and this might cause some ambiguity in the movements during run time. A similar study by Komura et al., proposed a martial arts training system based on motion capture [11]. The learner wears a motion-capture suit and a HMD. The virtual teacher appears alone in front of the user through the HMD. The virtual teacher location and rotation angle are fixed as well. This system analyzes the learner’s motion and offers suggestions and other feedback.

Collaborative physical task learning using mixed reality systems has been investigated in many fields as well. The results suggest such systems do enhance the task performance. In the dance learning field, Zhenyu et al. presented a collaborative dancing between remote dancers in a tele-immersive environment [20]. Here, a 3D representation of the dancers is captured in real time, then streamed, and rendered in a shared virtual space. This system also features a multi-surrounding display to help the dancers conveniently view the display from an arbitrary angle. In another study, Kirk et al. demonstrated how remote gestures influence the structure of collaborative discourse [10]. The results suggest that the use of remote gesture technologies does influence the structure of language used by the collaborating parties. In this system, only the helper hands’ view is projected into a fixed location on the worker’s desk area. The worker can’t mo ve or control the projected view.

On the other hand, our system focuses on how the virtual teacher should be presented when it moves several body parts. Some of the motions can be difficult to watch from a fixed viewing angle relative to the virtual teacher. However, this problem has not been pointed out very often and the solution has not been provided. The method presented in this paper provides a solution to this problem by automatically rotating the virtual teacher’s body in appropriate horizontal angle. Learners of physical-task movement can improve learning result by this method.

3. MAVT System’s Design Specification

A MAVT (Motion Adaptive Virtual Teacher) MR learning-support system has been built to test our automatic adjustment method. The system physical workspace is shown in **Fig. 1**. The system consists of two subsystems: the motion-capture system and the mixed-reality system (**Fig. 2**). The motion-capture system is used to track and record a person’s motions, and save them to files, while the mixed-reality system is used to process the recorded motion files and prepare the respective task’s motion sequence for the learner to practice.

3.1 The Physical-Task Learning Platform

The physical-task learning platform contains eight buttons [B_0-B_7] of 85 mm in diameter and 10 mm in height, placed on a table, as shown in **Fig. 3**. The buttons diameter was determined according to the average person’s hand width, to minimize uncertainty

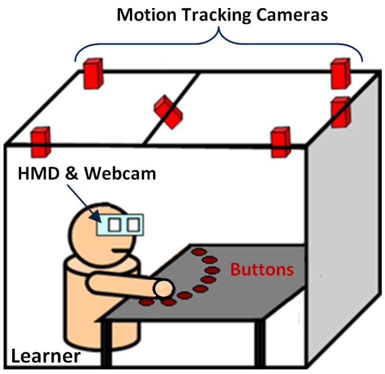

Fig. 1 The physical workspace of the physical-task learning-support system.

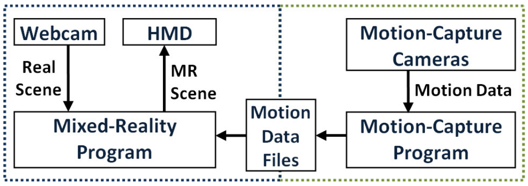

Fig. 2 The physical-task learning-support system's configuration overview.

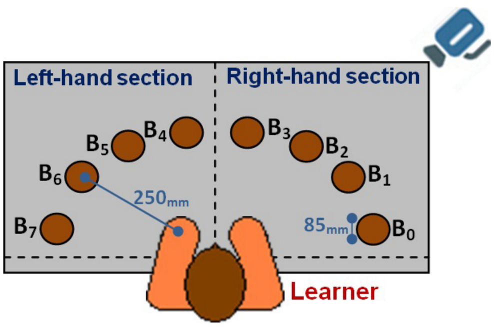

Fig. 3 The button distribution on the table.

in the view. For the learner to access the target buttons comfortably, the distance between each of the eight buttons and the learner's hands was set to 250 mm. The buttons were arranged as seen in the figure so that the physical motions are distributed over the learner's entire front space. In order to engage both the learner's hands in the physical-task learning, four buttons [B_0-B_3] were operated by the learner's right hand, and four other buttons [B_4-B_7] were operated by the learner's left hand. This generates the kind of motions that cover a wide range of real physical tasks.

In our push-button physical-task learning platform, the learner was seated in a fixed location in front of the table. The virtual teacher appeared at the learner's horizontal level. In such a setup the virtual teacher's lower body movements could be ignored, and all motions were carried out by the upper body, more specifically by the hands. The learner watched the teacher's upper-body motion and performed a similar motion in real time.

The push-button task was adopted as a simple generic example of physical-task motion whose errors can be measured quantitatively. Displaying the body motion in such tasks might not be necessary in general. In our experiment, the body motion was not considered as long as the learner used the correct hand to push the correct button. However, displaying the buttons and the upper-body together had the effect of making the task's instruction clearer and predictable [18]. Thus, displaying the upper body

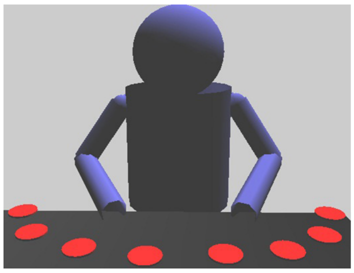

Fig. 4 The 3D virtual teacher's appearance.

motion in our experiment was considered appropriate.

3.2 Motion-Capture System Specification

The motion-capture system is a computer system connected to six NaturalPoint Optitrack^{TM} (FLEX: V100) optical motion-tracking cameras through a hub (OptiHub). These cameras are used to capture a person's motion by tracking visible reflective markers that are placed on his body.

The main features of the V100 camera are: shutter time, 1 ms; resolution, 640 × 480 pixels; latency, 10 ms; accuracy up to 2D sub mm; operating range from 15 cm to 6 m; frame rate, 100 Hz; and viewing angle, 45° field of view (FOV). The motion-capture computer system's main specifications are: hardware: CPU 2.2 GHz, RAM 1 GB; software: Windows Vista SP1 OS, Optitrack Baseline SDK, and Visual Studio 2008 (C#).

3.3 Mixed-Reality System Specification

A C++ program was developed to combine the real scene from the webcam, with the computer generated 3D virtual teacher, and display it through a HMD. We used the HMD iWear® VR920TM^{TM} in our system. The main features of the VR920^{TM} are: resolution, 640×480 pixels (equivalent to a 62 inches screen viewed at 2.7 m); weight, 90 g; frame rate, 60 Hz; and viewing angle, 32° FOV. The webcam employed is the clip-on iWear® CamAR^{TM} that mounts above the face of an iWear VR920 virtual reality system whose main features are: resolution up to 800 × 600 pixels; frame rate, 30 Hz; and viewing angle, 75 diagonal FOV. The mixed-reality computer system's main specifications are: hardware: CPU 2.8 GHz, RAM 2 GB; software: Windows XP SP3 OS, iWear® VR920^{TM} SDK, OpenCV1, and Visual Studio 2008 (C++).

3.4 The Virtual Teacher's Appearance and Motion

A recent study found that men's decisions are strongly affected by certain aspects of the appearance of the virtual avatar, while women's are not [12]. Another study found that attractiveness (and gender) has an effect on the way that virtual interactions occur on both sides [2]. Therefore, to minimize any effects of the virtual teacher-model's appearance on the task performance, a plain cylindrical 3D model was used in the experiment, as shown in **Fig. 4**.

Sub-motion units, which show the virtual teacher pushing one of the eight buttons, were prepared in advance by tracking and recording a real person's motion while he performed these actions. This created a smooth and realistic computer graphic avatar movement when the motion data was animated by the free soft-

Table 1 Sample motion-capture data (mm).

Frame #	Marker #: 1 Head X	Y	Z	2 Chest X	Y	Z	3 Right Shoulder X	Y	Z		8 Left Hand X	Y	Z
0	21.9	331.4	-161.6	3.4	55.1	-226.0	132.6	179.8	-119.1		-121.4	16.7	48.5
1	22.0	331.5	-161.8	3.5	55.2	-226.3	131.6	179.9	-119.2	…	-121.2	17.9	49.4
2	22.2	331.6	-162.0	3.6	55.3	-226.1	139.6	180.0	-119.4		-120.7	19.5	50.6
						:							
108	22.3	331.7	-162.2	3.5	55.4	-226.2	132.6	179.9	-119.2		-119.5	23.6	53.5
109	22.4	331.8	-162.3	3.4	55.6	-226.3	132.7	179.7	-119.3		-119.1	26.1	55.3

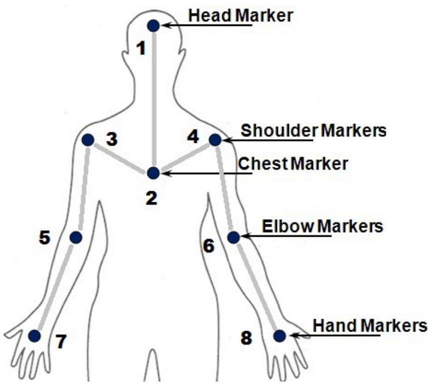

Fig. 5 The marker locations on the teacher's body.

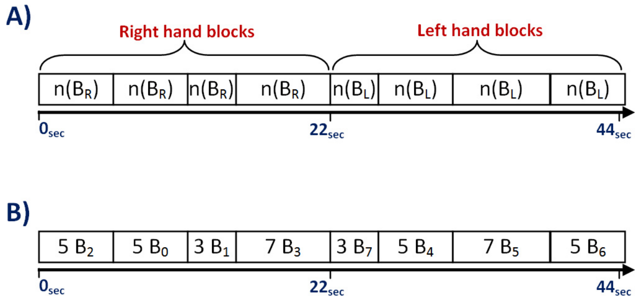

Fig. 6 (A) The motion task divided into eight blocks, where n represents the block size and has the value 3, 5, or 7. B_R is one of the right-handed sub-motion units. B_L is one of the left-handed sub-motion units. (B) A sample motion task.

ware RokDeBone [*1].

To adequately capture and animate the teacher's upper-body motions, a minimum of eight unique reflective markers were placed on the teacher's upper body, as shown in **Fig. 5**. The motion-tracking software 'OptiTrack© Rigid Body Toolkit' was used to capture the teacher's motions. The markers' 3-dimensional coordinate data (X, Y, and Z) were recorded at a 100 frame-per-second rate. **Table 1** shows samples of motion-capture data. Each line in the motion-data file represents one frame of motion data, and each frame contains the eight markers' location data. The recorded sub-motion unit's duration was 1.1 seconds on average (110 frames recorded at a 100 frame-per-second rate). Since there were eight buttons in our physical-task learning platform, eight recording sessions were conducted to produce eight unique sub-motion units; four sub-motion units were right-handed motions, and the remaining four sub-motion units were left-handed motions.

3.5 Producing Physical-Motion Tasks

In our MR system, the virtual teacher performs a gradual physical-motion task in front of the learner. Therefore a distinctive set of physical motion tasks had been produced at run-time. By using all the prepared basic sub-motion units, we systematically created a chain of sub-motions according to the following aims:

- We combined the prepared sub-motion units into variable-sized similar-motion blocks. In order to ensure that the user would not memorize the number of sub-motions within each block, we randomly employed a variable block size of 3, 5, or 7 sub-motion units.
- To avoid distracting the learner by frequently switching the used hand, we decided to create the physical-motion task out of two balanced parts. The first part was composed of four randomly-defined right-hand blocks, and the second part of four randomly-defined left-hand blocks.

Based on these aims, a total of 40 sub-motion units were combined to create a one-motion task. This produced a movie of 44 seconds' length (**Fig. 6**).

4. Automatic Adjustment Method Design

The automatic adjustment processing flow chart is shown in **Fig. 7**. The system is divided into two main processes: an initialization process and a run-time process. During the system initialization, the virtual teacher's captured motion data is retrieved from a file system. Next, the task motion data is split into small fixed-duration segments. For each motion segment, the teacher's optimal rotation angle is calculated. During system run time, the viewing angle of the each segmented teacher-task motion is automatically adjusted according to the pre-calculated angle, which is the side-view of the main virtual teacher's movement, and displayed.

4.1 The Virtual Teacher's Rotation Angles

Our method assumed that the virtual teacher is located (seated) at a specific fixed location and not moving; i.e., not completely moving from one location to another. Therefore we fixed the virtual teacher's location to the point of origin at the same learner's horizontal level. To adequately assess the automatic adjustment method using our generic physical-task motions, the virtual teacher's environment must be divided into a sufficient number of sectors in such a way that the following motion scenarios are enacted:

- Having a virtual teacher's physical motion move from a sector governed by the right-hand to another sector also governed by the right-hand; i.e., we need at least two sectors governed by the right hand in front of the learner. Similarly, we need at least two sectors governed by the left hand in

*1 http://www5d.biglobe.ne.jp/˜ochikko/rokdebone.htm

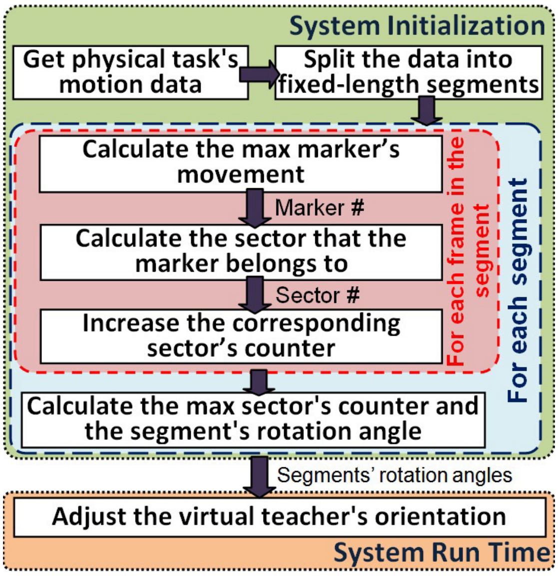

Fig. 7 The automatic adjustment processing flow chart.

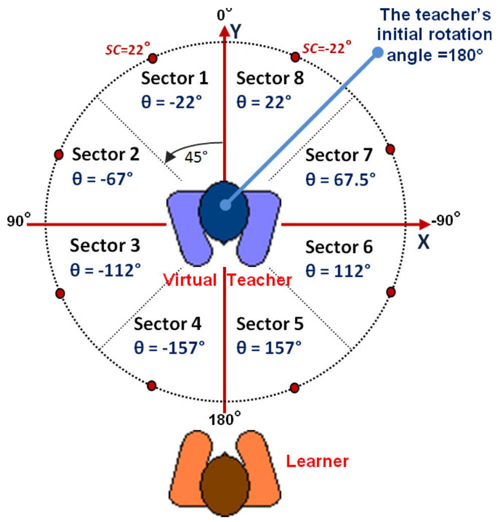

Fig. 8 The virtual teacher's environment divided into eight sectors.

front of the learner.

- Having a virtual teacher's physical motion move from a sector governed by the right-hand to a neighboring sector governed by the left-hand, and vice versa.

Based on these motion scenarios, the virtual teacher's environment was divided into eight equal sectors as shown in **Fig. 8**. Each sector covers a 45° range, and each has an associated counter (C_1-C_8). These counters were used to record the count of the virtual teacher's maximum moved marker in each sector during the automatic adjustment process. The sector with maximum counter value is considered the sector that contains the most important movements. Accordingly, the virtual teacher is rotated to the sector's predefined rotation angle (θ). The sector's predefined rotation angle (θ) had been calculated so that the sector's center angle faces the learner when selected using the following equation:

$$\Theta = 360 - SC \tag{1}$$

where SC is the sector's center angle.

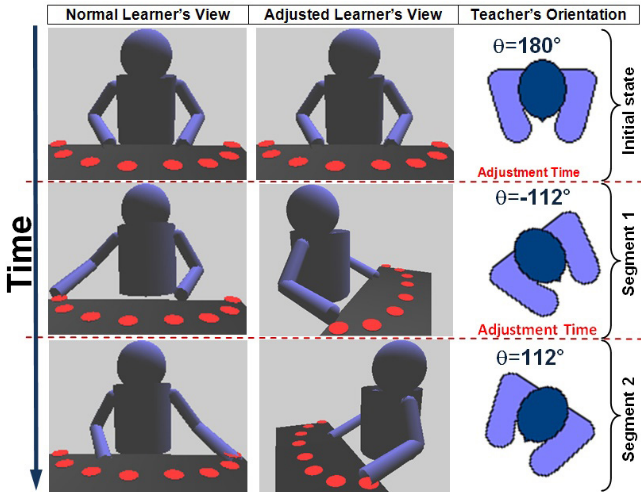

Fig. 9 The normal (fixed) learner's view compared to the adjusted view.

4.2 Calculating the Optimal Segment's Adjustment Rotation Angle

The automatic adjustment process starts by reading the segment's motion data frame by frame. For each marker's 3-dimensional coordinate data in the frame, the absolute marker's movement amount M_j in any direction is calculated based on the previous frame's marker data:

$$Mj = \sqrt{(Xcj - Xpj)^2 + (Ycj - Ypj)^2 + (Zcj - Zpj)^2} \tag{2}$$

where j is the marker number ranging from 1 to 8; X_{cj}, Y_{cj}, and Z_{cj} are the current frame j-marker's position data; and X_{pj}, Y_{pj}, and Z_{pj} are the previous frame j-marker's position data.

After calculating the frame's eight markers' absolute movement amounts, the maximum marker's movement MM_i is determined:

$$MMi = \mathrm{Max}\,(M_1, M_2, \ldots, M_8) \tag{3}$$

where i is the current frame number.

For this marker, which has the maximum absolute movement, we calculate the marker slope angle O_i with respect to the XY plane:

$$Oi = Arctan\left(\frac{Y_i}{X_i}\right) \tag{4}$$

Based on the calculated O_i angle, the counter of the sector that includes this angle is increased by 1. Once all the segment's frames are processed in the same manner, the maximum sector's counter value $C_{\max}$ is determined:

$$C_{\max} = \mathrm{Max}\,(C_1, C_2, \ldots, C_8) \tag{5}$$

The resulting sector with $C_{\max}$ is assumed to be that wherein the most important motion has occurred. Accordingly, the virtual teacher's rotation angle in the entire segment will be set according to the selected sector's predefined rotation angle (θ).

Figure 9 shows the resulting views during the first two segments of a preliminary test of the method. The virtual teacher's initial rotation angle was 180°. During the first segment, the virtual teacher used mostly his/her right hand over Sector 3. Therefore the virtual teacher's rotation angle was automatically adjusted to −112°. In the second segment, the virtual teacher used mostly his/her left hand over Sector 6, and in this case the virtual teacher's rotation angle was adjusted to 112°. In each of these cases, the learner confirmed that he was able to clearly see the critical elements of the virtual teacher's motion.

5. MAVT Experiment

To evaluate if the automatic adjustment method produces a better view, a comparative generic physical-task learning experiment was conducted. The first part of this learning experiment was performed using three predefined and fixed virtual-teacher rotation angles. The second part was performed using the virtual teacher's automatic adjustment method. The experiments were videotaped. A questionnaire was completed by the participants after each session. The error rates were compared and analyzed to find out any significant improvements between the conditions.

5.1 Participants

A total of 21 participants took part in this experiment as learners, 9 females and 12 males. The participants' ages ranged from 20 to 33 (mean = 24, s.d. = 3.5), and they were mostly undergraduate or postgraduate students. The participants were divided into two groups. One group performed the first part of the experiment, while the other group performed the second part. There were 11 members in the first group, comprised of 6 males and 5 females; and 10 members in the second group, comprised of 6 males and 4 females. All the participants were right-handed and had normal or corrected-to-normal vision.

5.2 Training Sessions

Because the participants were using this system for the first time, it was expected that they would become overly accustomed to the system after a while. To avoid this effect, training sessions involving the mimicking of simple physical task motions were first conducted. The training session's motion task consisted of 10 random-motion units. Each motion unit consisted of pushing one of the eight buttons. The virtual teacher appeared in front of the learner through the HMD. The learners were asked to correctly copy the virtual teacher's motions as quickly as they could. The virtual teacher performed one motion unit and waited until the learner performed the same motion. When the learner correctly performed the same motion, the system displayed the next motion unit. The training session ended once the learner correctly performed the 10 motions. The virtual teacher's rotation angle was fixed to 180° for the first group. For the second group, the virtual teacher's rotation angle was automatically adjusted for every motion unit. At the end of each session, the session's time and number of errors were calculated. Based on these values, the researcher decided whether the learner needed to conduct more training sessions or not.

The training sessions' results showed that learners became accustomed to the system after an average of 5 sessions for the first group and an average of 4.5 sessions for the second group, where no significant changes in the task's accomplishment time, or the number of errors, were reported. **Figure 10** shows the first group's average accomplishment time and average error rate per session. **Figure 11** shows the second group's average accomplishment time and average error rate per session.

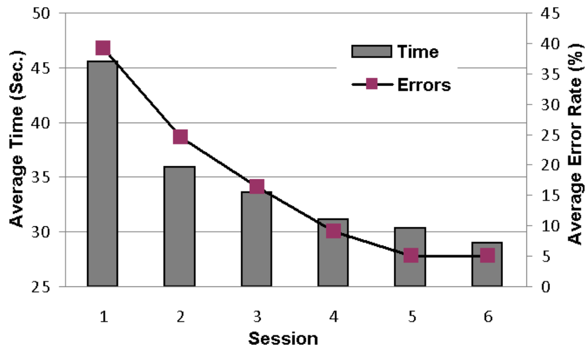

Fig. 10 The first group's average accomplishment time and error rate per training session.

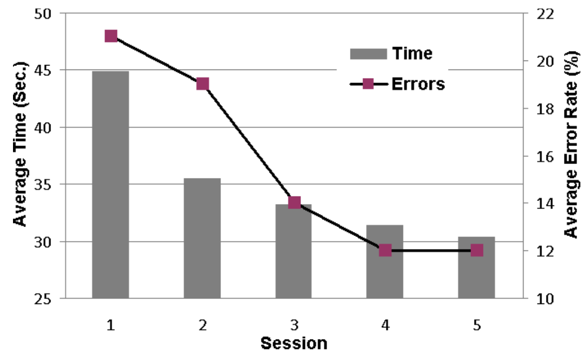

Fig. 11 The second group's average accomplishment time and error rate per training session.

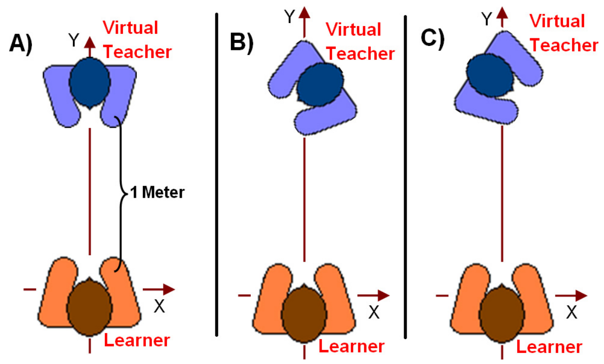

Fig. 12 The three fixed rotation-angle conditions: A) 180° B) 105° C) −105° rotation angle.

5.3 Fixed Rotation Conditions

It has been shown in a previous study that a virtual teacher-model's position and rotation angle have significant effects on physical-task learning [8]. That study suggested that the close side view of the virtual teacher is the optimal view for physical-task learning that involves one-hand motion. Based on this, we decided to assess the top three fixed rotation-angle conditions from that study (**Fig. 12**). The first condition has a 180° rotation angle, the second condition a 105° rotation angle, and the third a −105° rotation angle. The first condition represents a normal setup wherein the teacher is located in front of the learner, the second condition represents a teacher's left-hand focused view, and the third condition represents a teacher's right-hand focused view. In the three conditions, the virtual teacher was placed at one meter's virtual distance away from the learner. **Figure 13** shows

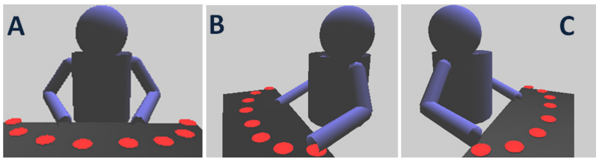

Fig. 13 The virtual teacher's appearance with: A) 180° B) 105° C) −105° rotation angle.

the resulting virtual-teacher view in the three fixed rotation-angle conditions.

Each participant in this part of the experiment performed three physical-task learning attempts by mimicking the virtual teacher's motions. The virtual teacher appeared in front of the learner through the HMD with a fixed rotation-angle. Each learner performed the experiment in each of the three fixed rotation-angle conditions, one by one. The virtual teacher continuously performed one of the pre-generated motion tasks for 44 seconds in front of the learner. The learners were asked to watch and simultaneously push the correct button, and as many buttons as the virtual teacher pushed. The experimental sessions were recorded on tape. Afterward, the sessions were reviewed and the task's error rate was calculated for each condition.

5.4 Automatic Adjustment Condition

This part was similar to the fixed rotation-angle conditions experiment, except that here the participants performed one physical-task learning attempt only. In this part of the experiment, the virtual teacher's rotation angle was automatically adjusted during the run time. The learners were asked to watch and simultaneously push the correct button and as many buttons as the virtual teacher pushed. The experimental sessions were recorded on tape. Afterward, the sessions were reviewed and the task's error rate was calculated.

6. Results and Discussion

Our primary goal was to find out whether or not the automatic adjustment method would minimize the number of committed errors when providing a better view. Minimizing the number of errors was assumed as one factor in improving physical-task learning. The statistical results of the two experimental groups were analyzed to determine whether using the automatic adjustment method significantly reduced the number of errors or not.

6.1 Experiment's Statistical Results

The fixed rotation-angle experiment's results are shown in **Fig. 14**. The average error rate in each condition was calculated to be: for the first condition (180°), 12.27% (s.d. = 6.9%); for the second condition (105°), 12.5% (s.d. = 4.6%); and for the third condition (−105°), 12.5% (s.d. = 7.1%). First, we tested the error rate's results of the three fixed rotation-angle conditions using ANOVA. The analysis confirmed no significant difference between the three conditions' average error rate ($F(2,30) = -0.0047$, $p < 0.01$). Therefore we summed up all the fixed-rotation conditions' data to be used as the fixed condition's data. This was to be used to compare with the automatic-adjustment condition's data. On the other hand, **Fig. 15** shows the automatic-adjustment experiment's result. The average error rate was calculated to be 6.0% (s.d. = 2.7%). The t-test (assuming unequal variances) was used to compare the means of the two conditions (the automatic adjustment and the joined fixed rotation condition). We found that using the automatic adjustment method decreased the average error rate, and the average error rate was significantly different ($t(31) = 5.1$, $p < 0.01$) (**Fig. 16**).

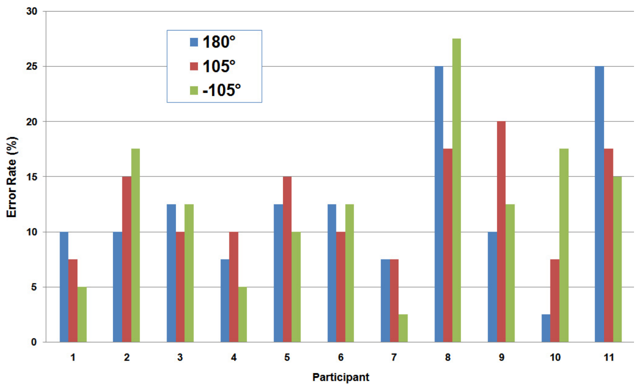

Fig. 14 The fixed rotation-angles' error rate per participant.

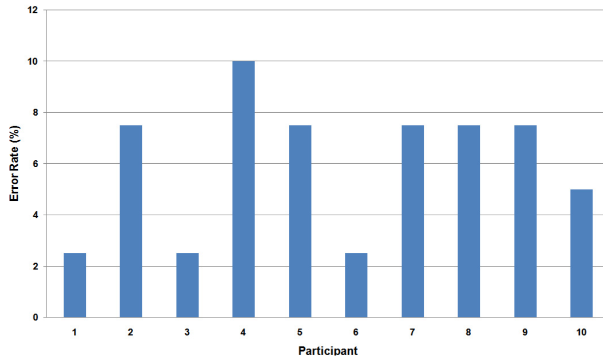

Fig. 15 The automatic adjustment's error rate per participant.

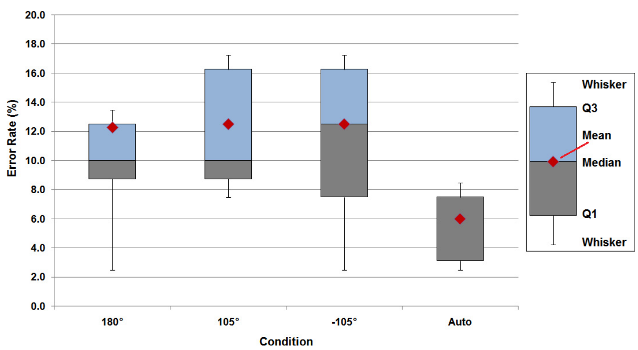

Fig. 16 The average error rate per condition.

6.2 Errors

We found that the errors observed in the experiment could be categorized into three types, as follows (Note that the learner was supposed to watch the virtual teacher and simultaneously push the correct button in any manner he/she preferred as long as he/she used the correct hand; the learner's body motion itself was not considered.):

- Type **A** error: When the learner pushes a different button than the intended one.
- Type **B** error: When the learner pushes a correct button but

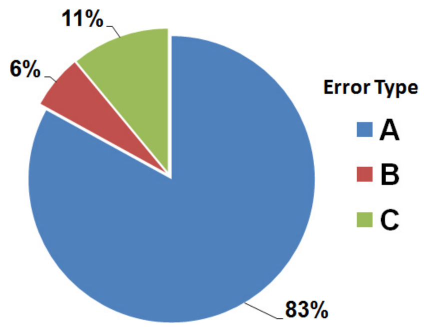

Fig. 17 The percentage of the experiment's error types.

with the wrong hand.

- Type **C** error: When the total number of learner's button pushes does not match the exact number performed by the virtual teacher. This covers the following two cases:
  - When the total number of learner's pushes is more than the correct performed number. In this case, the extra pushes are considered errors.
  - When the total number of learner's pushes is less than the correct performed number. In this case, the missing pushes are considered errors.

Figure 17 shows the error details. The Type **A** error, pushing the wrong button, was found to be the most common error across all the conditions with 83% of the total errors. This error typically seemed to occur when the learners could not see the virtual teacher's motion clearly. The Type **B** error, using the wrong hand, made up 6% of the total errors. In this regard, we found that some of the learners tended to use their right hands more than their left hands. The Type **C** error, pushing more/less buttons, made up 11% of the total errors. In this type of error, most of the learners failed to push a button when they became confused and could not decide which one of the buttons was the correct one. On the other hand, few learners pushed the button extra times.

A thorough analysis was conducted in order to determine what had caused some of the repeated errors in our experiment, and whether or not the automatic adjustment method had resolved those problems. In the fixed rotation-angle conditions, we noticed that some of the learners spent extra time at the beginning. This might be because they needed this time to figure out the experiment's initial setup, and which hand they were supposed to use, despite the pre-session instructions, and the fact that the time before the first motion unit was displayed was the same in each session. Nonetheless, this may have caused some of them to miss the first motion unit in some cases. On the other hand, the automatic adjustment method provided a close and direct view of the initial virtual-teacher motion, which in turn minimized the confusion that occurred under the fixed-rotation conditions.

Our generic experiment involved pushing the same button 3, 5, or 7 times. It was observed that the number of buttons pushed was sometimes one more than the correct number, when the correct numbers were 3 or 5. Six cases were found in the fixed rotation-angle conditions, and two cases were found in the automatic adjustment condition. Although the result was not statistically significant because of the small number of cases, the automatically adjusted view might alleviate this type of error.

Table 2 The questionnaire results.

	Fixed (N=10)			Proposed (N=8)		
	Disagree	Neutral	Agree	Disagree	Neutral	Agree
Q1) Wearing the HMD and moving around was easy and comfortable	6	2	2	3	2	3
Q2) The virtual teacher's motion was easy to follow	2	4	4	1	3	4
Q3) The virtual teacher's motion was slow	3	4	3	3	3	2
Q4) The experiment's session duration was short	1	5	4	0	4	4

The learners seemed to have some difficulty in recognizing the farthest two buttons in the view (B_0 and B_1) in the second fixed rotation-angle condition (105°). The same difficulty was observed in the third fixed rotation-angle condition (−105°), wherein the farthest two buttons were B_7 and B_6. The Type **A** error occurred 9 times in these conditions, and only 3 times in the automatic adjustment condition.

There was a case in which the current proposed method could not provide a good view. When the motion segment contained buttons from both the far ends (B_0 and B_7), the minority of motions suffered a bad view because the method gives the majority a good view .

6.3 Participant Feedback

The questionnaire consists of the four questions shown in **Table 2** as well as a free-feedback field. Table 2 shows the answers to the questions. Though the number of participants was 21, we excluded a few incomplete questionnaires and used 18 as the result.

We noted a number of tendencies in the answers, and confirmed the appropriate design of the experiment. Although only a three-point scale was used for answering the questions, and answers were not analyzed statistically given their small number.

Regarding the HMD, many participants felt it was somewhat troublesome to wear. They mentioned that the HMD's weight was rather cumbersome, which is a common reaction to the HMD in general. Some participants noted that the HMD's resolution was adequate but that they had expected better. The score here seemed somewhat less for the fixed rotation-angle conditions. This might be because the relatively crude resolution makes it more difficult to see the more distant, and thus smaller, motions of the virtual teacher in the fixed conditions. The majority reported some feelings of anxiety, as this was the first time they had used an augmented reality system. Regarding the virtual teacher's view and motion, the participants seemed to feel somewhat easier in following the virtual teacher's motion with the proposed method. Some participants felt that the motion task was too simple, but the motion speed was confirmed as appropriate for the task. Regarding the last question, on the sessio n's duration, it was confirmed that the experiment was not too long to have an effect on the result.

6.4 System Limitations

Our proposed method assumed that the learner will sit and see the virtual teacher in front of him at the same horizontal sight level as if in a real situation. The method only controls the view's horizontal rotation angle. The vertical rotation and orthogonal view were not considered in this study. Having this assumption, the method still can provide a good viewing angle even for cross-sectional motion. If a motion segment ends up with multiple sectors with the same maximum motion counters, the method will select the most central sector among them.

The method also assumed a gradual slow physical motion. To support fast motions more aspects would need to be considered, such as the segment length. In this evaluation we considered only fixed-length segments, however a more dynamic, variable-segment length, based on the amount of motion, may improve the method outcome. In the future, we will consider implementing a dynamic automatic adjusting method in some real physical-task learning experiment.

7. Conclusion

In this paper, we proposed a method for automatically adjusting the virtual teacher's rotation angle when the virtual teacher is demonstrating physical-task motion. This method will ensure that the learner sees most of the teacher's motion from an optimal close-viewing angle.

To determine whether the automatic adjustment method would produce a better view, a physical-task learning experiment was conducted. The first part of the learning experiment was performed using three predefined, fixed-rotation angles for the teacher view. The second part was performed using the teacher's automatic adjustment method. The result showed that the automatic method scored a lesser error rate compared to the fixed-rotation angle method.

The former method is significant for physical-task learning because such learning is mainly done by observation. The method is also useful for remote collaborative physical tasks involving full-body motion. Moreover, when the learner has his/her own physical objects in hand, it might be difficult for him/her to control the viewing angle at the same time, even if the system provides an angle-control function to the learner. The proposed method helps the learner in this situation; and is, again, valuable for similar situations involving collaborative physical tasks.

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