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Setting the best view of a virtual teacher in a mixed reality physical-task learning support system

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ABSTRACT

In this research, we investigated the virtual teacher's positions and orientations that led to optimal learning outcome in mixed-reality environment. First, this study showed that the virtual teacher's position and orientation have an effect on learning efficiency, when some teacher-settings are more comfortable and easy to watch than others. A sequence of physical-task learning experiments have been conducted using mixed-reality technology. The result suggested that the virtual-teacher's close side-view is the optimal view for learning physical-tasks that include significant one-hand movements. However, when both hands are used, or rotates around, a rotation-angle adjustment becomes necessary. Therefore, we proposed a software automatic-adjustment method governing the virtual teacher's horizontal rotation angle, so that the learner can easily observe important body motions. The proposed software method was revealed to be effective for motions that gradually reposition the most important moving part. Finally, to enhance the proposed method in the future, we conducted an experiment to find out the effect of setting the vertical view-angle. The result recommended that the more motion's rotation involved the more vertical view angles are wanted to see the whole motion clear.

1. Introduction

Mixed reality (MR) refers to the process of merging computer-generated (CG) graphics onto a real-world scene to produce new environments and visualizations where physical and digital objects co-exist and interact in real time. A virtuality continuum was proposed by Milgram and Kishino (1994), with the real environment at one end and the virtual environment at the other. Augmented reality (AR) and augmented virtuality (AV) are situated in between, depending on whether reality or virtuality is being modified (Fig. 1).

Physical-task learning that utilizes virtual reality and/or mixed reality technology has been actively researched. The use of purely synthetic scenarios in training systems reduces the authenticity of learning or training exercise (Gelenbe et al., 2004), while 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, using sensors and virtual reality (Watanuki, 2007; Ohsaki et al., 2005; Chambers et al., 2012). The results suggest that MR is suitable for supporting physical task learning. Thus, we have developed a physical-task learning-support system using MR (Inoue and Nakanishi, 2010). The system visualizes a life-sized CG 3D virtual teacher model in front of the learner. Since appropriate feedback information is important for effective and smooth task learning (Watanuki, 2007), the developed system is also interactive, tracking the learner's movements and providing basic feedback.

The motivated question behind this research was whether a virtual teacher's position and rotation affect the physical-task learning outcome or not. We assumed that some teacher setups are better than others and accordingly this will affect the learning outcome in such environment. The virtual teacher setups that lead to optimum learning outcome were not determined before. Therefore, we run this research to accurately identify these setups and to study all the parameters that lead to better learning outcome when mimicking a virtual teacher using MR. The outcome of this research will greatly affects the way the physical-task learning systems are implemented for collaborative physical-task learning. Being able to accurately, safely and speedily perform the training are major demands especially in the domains of medicine (de Almeida Souza et al., 2008; Song et al., 2009), military (Cheng et al., 2010), industry (Chambers et al., 2012), etc. To perform such physical tasks, the learner must watch carefully and perform the same actions, in the same exact order, as are presented by the virtual teacher.

In this paper, we first discussed the potential orientations of the virtual teacher model in a MR system, to determine the virtual

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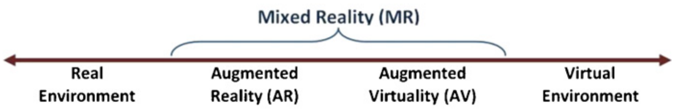

Fig. 1. The virtuality continuum.

teacher's optimal position and rotation for physical-task learning. Optimalization was measured by the required time to accomplish the physical-task, and the number of committed errors. To investigate the effect of the virtual teacher's position and rotation, two experiments were conducted; the first, to narrow down the large number of possible locations in which the virtual teacher may be presented; and the second, to determine the virtual teacher's optimal position and rotation. To determine whether the virtual teacher's solid appearance affected the results, experimental comparisons with a semi-transparent virtual teacher were also conducted in the study.

The experiments' 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 hands, or rotates around, then a rotation-angle adjustment method becomes necessary. Therefore, we then introduced a novel method of automatically adjusting the virtual teacher-model's rotation angle during run time (Nawahdah and Inoue, 2011). 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.

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

As explained, a major contribution of this research is improving a mixed reality system and software for collaborative physical-task learning. Thus this paper is relevant to this journal, The Journal of Systems and Software, by demonstrating one aspect of the improvement of such a system and software. Because this research specifically focuses on how a virtual teacher, a collaborative counterpart, should be displayed in the software system, this paper best fits to this special issue on collaborative computing technologies and systems.

2. Related works

There have been various studies in various domains done on virtual reality and MR-based skill/task learning and training support and a number of systems have been developed, e.g., in the industry domain: constructing machine-maintenance training system (Ishii et al., 1998), metal inert gas welding training system (Chambers et al., 2012), object assembly training system (Jia et al., 2009), overhead crane training system (Dong et al., 2010), firefighting tactical training system (Yuan et al., 2012), esthetic industrial design (Fiorentino et al., 2002), job training system for casting design (Watanuki and Kojima, 2006); in the science and education domain: electrical experimental training system (Kara et al., 2010), application of geography experimental simulation (Huixian and Guangfa, 2011), collaborative learning (Jackson and Fagan, 2000); in the medicine domain: ultrasound guided needle biopsy training system (de Almeida Souza et al., 2008), baby feeding training system (Petrasova et al., 2010), endoscopic surgery simulation training system (Song et al., 2009); in the tourist domain: tourist guide training system (Minli et al., 2010); in the military domain: missile maintenance training system (Cheng et al., 2010); in the sports domain: Kung-Fu fight game (Hamalainen et al., 2005), martial arts (Chua et al., 2003; Kwon and Gross, 2005; Patel et al., 2006), physical education and athletic training (Zhang and Liu, 2012), golf swing learning system (Honjou et al., 2005); in the dance domain: dance training system (Nakamura et al., 2005; Chan et al., 2010), collaborative dancing (Yang et al., 2006); in the cooking and eating domain: augmented reality kitchen (Bonanni et al., 2005), augmented reality flavors (Narumi et al., 2011), augmented perception of satiety (Narumi et al., 2012), etc. Many of these systems have employed a virtual teacher to perform the physical task in front of the learner (Yang and Kim, 2002; Nakamura et al., 2003; Honjou et al., 2005; SangHack and Ruzena, 2006; Chua et al., 2003). Some of these systems enhance the learning experience by virtually displaying related information and providing necessary feedback, which have been proved to be useful in the respective domains.

Horie et al. (2006), e.g., proposed an interactive learning system for cooking in an MR environment, using video data extracted from TV cooking programs. 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 and Sano (2008), and in that, a virtual agent performing actions corresponding to the current cooking step is displayed in a fixed location at a table as well.

Regarding dance skills acquisition, Nakamura et al. (2003) developed a 3D dance model in the virtual world. The teacher and learner's avatar were projected side by side on a projector screen. However, such video settings only allow the learner to watch the teacher, while immersive virtual reality allows the learner to interact with the teacher and the environment, as well as to perform novel functions such as sharing body space with the teacher. This capability has been introduced in a 3D immersive system developed by Patel et al. (2006), to teach moves from the Chinese martial art of 'Tai Chi'. In this system, the learner sees four stereoscopic human representations: an image of him and a teacher from behind, as well as a reflection of the front of these avatars in a virtual mirror. The image is displayed on a screen in front of the physical workspace. The results of this research showed that people learned more in the immersive virtual reality system in comparison to traditional 2D video systems.

In the aforementioned studies, the learner must look at a screen in front of him to see the virtual world. Multi-display systems, on the other hand, offer the learner a chance to conveniently view from arbitrary angles, and coordinate their body movements. This technique was implemented in a collaborative dancing system developed by Zhenyu et al. (2006). Here, a 3D representation of the dancers is captured in real time, then streamed, and rendered in a shared virtual space. For mobility and ease-of-watching, Chua et al. (2003) proposed a wireless virtual reality system for teaching Chinese 'Tai Chi'. 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. However, the results suggested that the techniques employed had no substantial effect on learning physical tasks. In another study, by Kimura et al. (2007), 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. The results confirmed that the superimposed method is the most effective for the repetition of partial movements, while the others are effective for whole movements. All of these methods, except for the mirror format, were incorporated into our research. The mirror format was omitted because of the assumption that the mirror effect would cause learner uncertainty, and this would diminish learning performance.

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, the ability to sense the learning task and its progress is built in to virtual reality-based learning support systems (Watanuki, 2007; Ohsaki et al., 2005; Nakamura et al., 2003). 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 (Watanuki, 2007). Such motion-capture technology is used in a dancing training system developed by Chan et al. (2010). 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. A similar study, by Komura et al. (2006), proposed a martial arts training system based on motion capture. The learner wears a motion-capture suit and HMD. The virtual teacher appears, alone, in front of the user, through the HMD. This system analyzes the learner's motion and offers suggestions and other feedback. In our research, the task learning and its progress are sensed using a motion capturing system as well. The captured data are analyzed, and the system provides the learner with basic tone feedback, notifying her/him whether her/his performed motion was correct or not.

On the other hand, our research focuses on how the virtual teacher should be presented when it moves single or several body parts. For some simple motions a close side-view fixed viewing angle might be sufficient to clearly watch the virtual teacher from (Inoue and Nakanishi, 2010). But for other motions, a more flexible viewing angle has to be considered (Nawahdah and Inoue, 2011). 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. The vertical rotation angle adjustment has also considered for some specific cases as well. As a result, the learners of physical-task movement can improve learning by this method.

3. MAVT system design specifications

In this section, we discuss the MAVT (motion adaptive virtual teacher) MR learning-support system that we built to be used in our generic physical-task experiments. We first introduce the learner–virtual teacher model that we employed in this research. Then we give details on system design specifications. Finally we show the selected virtual teacher's appearance and motion.

3.1. Learner–virtual teacher model specification

Fig. 2 shows the learner–virtual teacher model employed in this research. In this model, d represents the distance between the centers of the learner and the virtual teacher model; θ_1 represents the shifting angle between the front direction of the learner and the virtual teacher model; and θ_2 represents the rotation angle of the virtual teacher model around himself.

In this model, the learner will be located at a fixed real location while the virtual teacher will be relocated virtually according to the mentioned parameters (d, θ_1, and θ_2). We also fixed the virtual teacher's size and height-level to mimic a normal person's size, on the same level, according to the virtual distance between the real learner and the virtual teacher. Given that the maximum human horizontal viewing angle is about 200° (Kiyokawa, 2007), the natural constraint of θ_1 range was set to ±100°. Examples of the virtual teacher model's relative conditions are shown in Fig. 3.

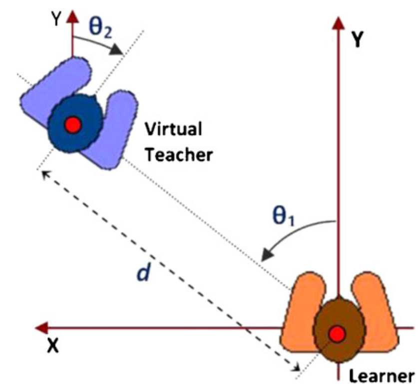

Fig. 2. The learner–virtual teacher model.

3.2. Physical-task learning support system design specifications

A physical-task learning support system was built for use in generic physical-task learning experiments (Inoue and Nakanishi, 2010). Fig. 4 shows the system's physical workspace. The system consists of two subsystems: the motion-capture system and the mixed-reality system (Fig. 5). 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.

3.2.1. The physical-task learning platform

The physical-task learning platform contains a number of buttons placed on a table. The push-button task was adopted as a simple generic example of physical-task motion whose errors can be measured quantitatively. The virtual teacher appeared at the

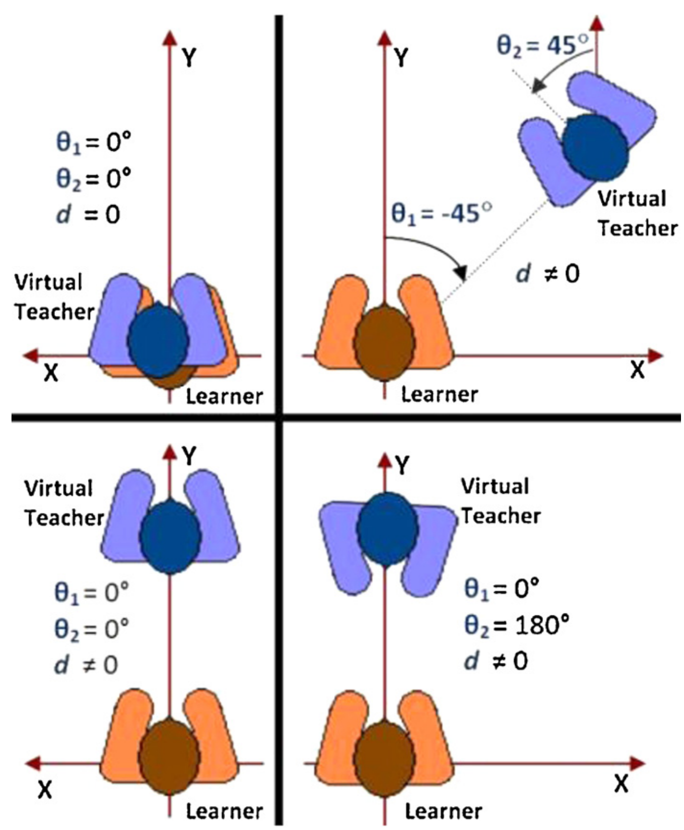

Fig. 3. Examples of virtual teacher's conditions.

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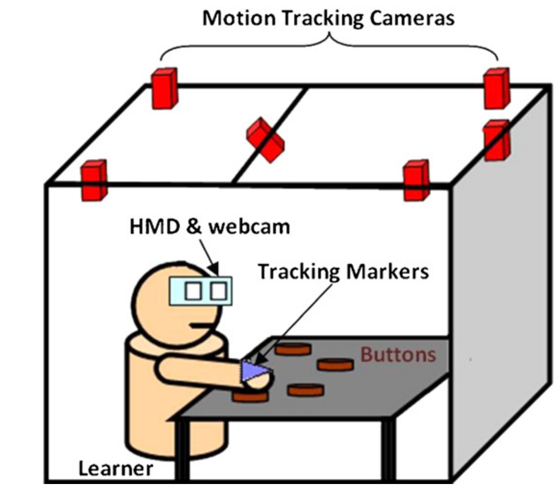

Fig. 4. The physical workspace of the physical task learning support system.

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. Displaying the body motion in such tasks might not be necessary in general. In our experiments, 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 (Yamashita et al., 2010). Thus, displaying the upper body motion in our experiments was considered appropriate.

3.2.2. Motion-capture system

The motion-capture system is a computer system connected to six NaturalPoint Optitrack™ (FLEX: V100) optical motion-tracking cameras through a hub (OptiHub). These cameras are used to detect the learner's motion within the captured volume area by tracking visible reflective markers that are placed on the learner's body. 7/16″ diameter, premium reflective sphere markers are placed on the learner's hand. Three markers placed at the vertices of a triangle are used to accurately capture the hand's position and direction. A program written in C# receives the captured-motion data from the cameras and processes it. This program is used to determine which button the learner has pushed, and send these data to the mixed-reality system.

The main features of the V100 camera are: shutter time, 1 ms; resolution, 640 by 480 pixels; latency, 10 ms; accuracy up to 2D sub mm (depending on the marker size and distance to camera); operating range, from 15 cm to 6 m (depending on the marker size); 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#).

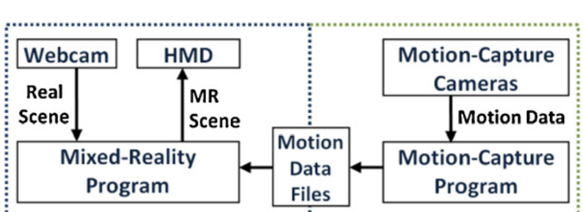

Fig. 5. The physical-task learning support system's configuration overview.

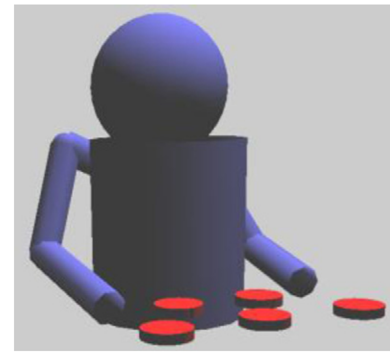

Fig. 6. The computer-generated 3D virtual teacher's appearance.

3.2.3. Mixed-reality system

The mixed-reality system is connected to a webcam and HMD. The webcam is used to capture the learner's view of the real world. The mixed-reality system is responsible for managing the 3D virtual teacher's physical motion task, which is displayed to the learner through the HMD. The system has flexibility in displaying the virtual teacher, based on the learner–virtual teacher model described above. The distance between the learner and virtual teacher may be configured to 0, 1 or 2 m. The virtual teacher's shifting angle can vary over a range of ±100°, and the virtual teacher's rotation angle can vary over the full range of 360°. The system can also display the virtual teacher at two levels of opacity: solid and 50% transparent.

A C++ program was developed to combine the real scene from the webcam, with the generated 3D virtual teacher. We used the HMD iWear® VR920™ in our system. The main features of the VR920™ are: resolution, 640 by 480 pixels (equivalent to a 62″ screen viewed at 2.7 m); weight, 90 g; frame rate, 60 Hz; and viewing angle, 32° FOV. The webcam employed is a Logitech® Quickcam Pro9000, whose main features are: resolution, high-definition video (up to 1600 by 1200 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™ SDK, OpenCV1, and Visual Studio 2008 (C++).

3.3. 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 (MacDorman, 2010). Another study found that attractiveness (and gender) has an effect on the way that virtual interactions occur on both sides (Banakou and Chorianopoulos, 2010). Therefore, to minimize any effect of the virtual teacher model's appearance on the task performance, a plain cylindrical computer-generated 3D model was used in our experiments, as shown in Fig. 6.

The virtual teacher's motion was randomly generated by combining basic-motion units during system run-time. Each of these motion units, which show the virtual teacher pushing one of the buttons, was prepared in advance by tracking and recording a real person's motion while she/he performed these actions. This created a smooth and realistic motion.

To adequately capture and animate the real teacher's upper-body motions, a minimum of 8 unique markers were placed on the teacher's upper body, as shown in Fig. 7. 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 8 markers' location data. The motion-tracking software 'OptiTrack© Rigid Body

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Table 1
Sample motion-capture data (mm).

Frame #	Marker #: 1 Head			Marker #: 2 Chest			Marker #: 3 Right shoulder				Marker #: 8 Left hand		
	X	Y	Z	X	Y	Z	X	Y	Z		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	35	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

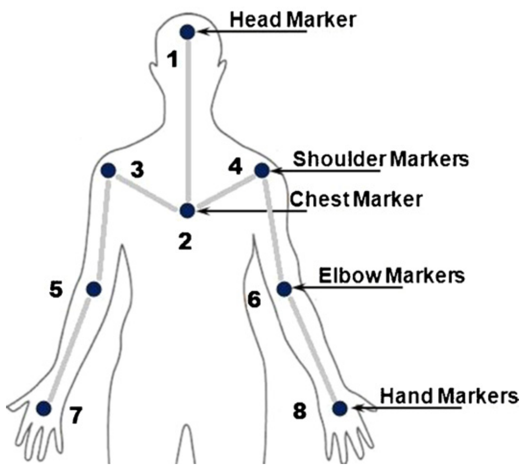


Fig. 7. The marker locations on the teacher's body.

Toolkit' was used to capture the teacher's motions. Core scenes from the teacher's motion-unit recording sessions are shown in Fig. 8. The recorded motion data were animated by the free software RokDeBone.[1]

4. Determine the virtual teacher's optimal position and rotation

Two experiments were conducted to investigate the effect of the virtual teacher's position and orientation in MR physical-tasks learning. The first experiment was employed to narrow down the large sample number of possible conditions, while the second experiment was conducted to evaluate the top-rated conditions identified in the first experiment, as well as other conditions defined in a previous, related study.

4.1. Experiment 1: narrowing down the virtual teacher's possible conditions

This experiment was conducted to investigate the range of virtual teacher positions and rotations most comfortable and instructive for the learner, during physical-task learning sessions.

4.1.1. Specification of the virtual teacher's conditions

In our model, the virtual teacher's positions and rotations can vary within the previously mentioned parameters (d, θ_1, and θ_2). These parameters produce an enormous number of conditions. Therefore, a systematic sampling method was used to reduce the number of evaluated conditions in this experiment. The distance d was sampled at 0, 1, and 2 m. The shift angle θ_1 was sampled at $0°$, $\pm 30°$, $\pm 45°$, and $\pm 60°$. The rotation angle θ_2 was sampled at $0°$, $\pm 45°$, $\pm 90°$, $\pm 135°$, and $180°$. This produced a total of 120 conditions (15 positions × 8 rotations). Fig. 9 shows the 120 conditions where the learner is located at the origin.

4.1.2. Participants

A total of 4 participants were hired to participate in this experiment. The participants were 4 male graduate students whose ages ranged from 23 to 28 years. All the participants were right-handed and had normal or corrected to normal vision.

4.1.3. Procedure

The physical-task support learning system we developed was used to present a 3D virtual teacher model performing hand-movement tasks in each condition, through the HMD. Since we had many possible conditions to test, and the required result was a range of conditions, a subjective evaluation was employed. In this experiment, each condition was rated on a 7-point Likert scale, separately, by each participant, based on how comfortable and well-informed they felt in mimicking the virtual teacher's physical-task of pushing the buttons. The participants were not required to finish each motion task and they were allowed to watch it as long as they need to evaluate the conditions. The evaluation scale was 1 "very confusing", 2 "confusing", 3 "somewhat confusing", 4 "neither", 5 "somewhat clear" 6 "clear", and 7 "very clear". After the evaluation process was completed, the average was calculated for each condition, and those conditions with a score of 4 or higher were considered good conditions.

4.1.4. Results

The conditions' average evaluation distribution is shown in Fig. 10, where each value represents the average value of the 4 evaluators' results for each condition. Regarding the distance d, most of the top-rated conditions were close to the learner (1 m). Regarding the virtual teacher's shifting angle θ_1, most top-rated conditions were close to the learner's center-view ($\pm 30°$). And regarding the teacher's rotation angle θ_2, the side-view of the 3D virtual teacher model seemed to be preferred ($\pm 90°$).

4.2. Experiment 2: determining the virtual teacher's optimal condition

The objective of this experiment was to investigate and determine the virtual teacher's optimal position and rotation, for the highest learning performance in a mixed reality environment.

4.2.1. Specification of the virtual teacher's conditions

Fig. 11 shows the conditions that were tested in this experiment. The top-rated conditions defined by the first experiment were considered and reduced to eight conditions by merging similar location conditions. Conditions 1–4 were selected to investigate the effect of changing the virtual teacher's shift angle. Conditions 5 and 6 were selected to investigate the effect of the distance from learner to teacher. Conditions 7 and 8 were selected to study the effect of teaching from the side view. Conditions 9–11 were considered

[1] http://www5d.biglobe.ne.jp/~ochikko/rokdebone.htm.

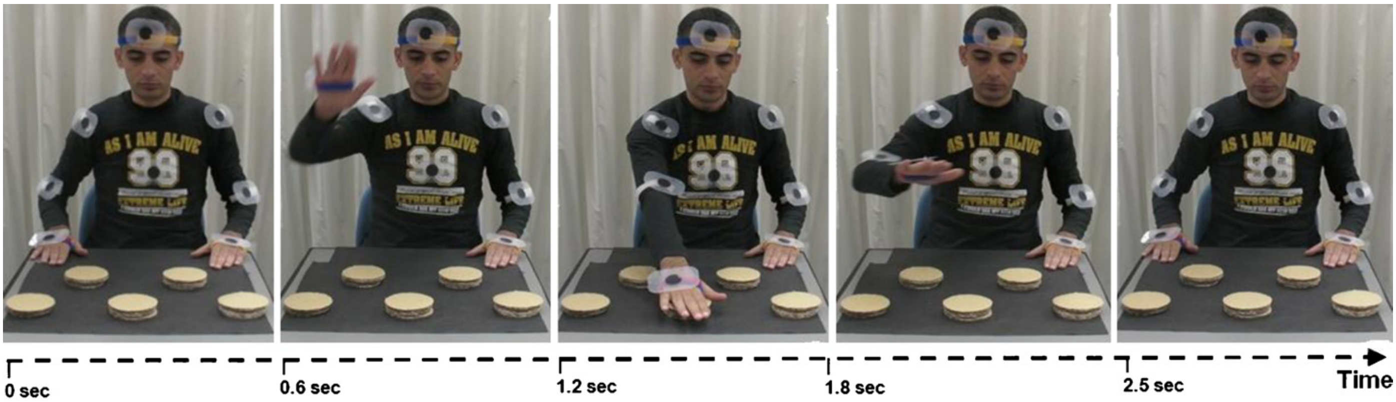


Fig. 8. Core scenes from one of the teacher's recording sessions.

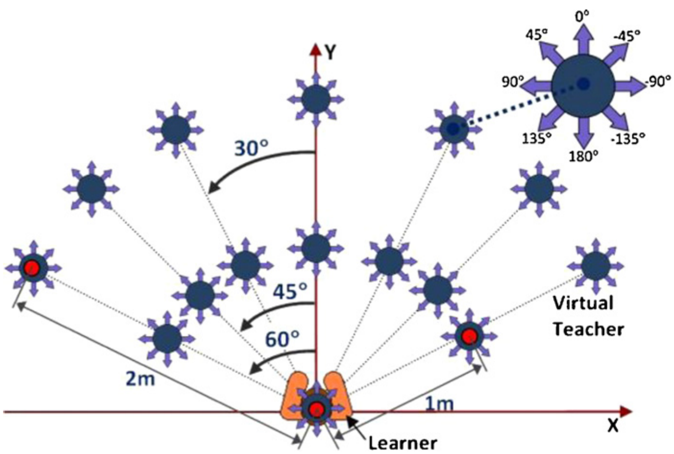


Fig. 9. The 120 evaluated conditions in the first experiment.

as a result of previous, related research (Kimura et al., 2007; Chua et al., 2003; Yang and Kim, 2002), in which they were positively evaluated in a virtual reality environment. Condition 9 represents a natural configuration in which the learner is located behind the teacher. Condition 10 represents another natural configuration, in which the learner is located in front of the teacher. Condition 11 represents a superimposed configuration, in which the teacher is virtually superimposed on the learner's body.

4.2.2. Participants

A total of 15 participants took part in this experiment, 7 females and 8 males. The participants' ages ranged from 20 to 28 (mean = 23, s.d. = 3.1), and they were all undergraduate or graduate students. All the participants were right-handed and had normal or corrected to normal vision.

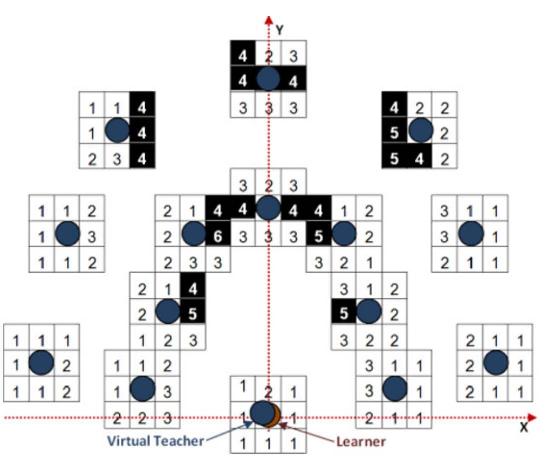
4.2.3. Experimental physical-task specification

A physical task-learning platform containing 5 buttons [B_1–B_5] placed on a table in two rows was used in this experiment (Fig. 12). The horizontal space between the buttons is 12 cm, and the vertical space between the two rows is 9 cm. The buttons were arranged in this way, so that the physical motions are distributed over the learner's entire front space. This generates the kind of motions that cover a wide range of physical tasks.

Since there were 5 buttons, 5 recording sessions were conducted to produce 5 motion units. An experimental virtual teacher's physical-task motion was randomly generated by combining 10 basic-motion units during system run-time. Fig. 13 shows a sample experimental physical task.

4.2.4. Procedure

Because the participants were using this system for the first time, it was expected that they would become accustomed to the system after a while. To avoid this, training sessions involving the mimicking of physical task motions were first conducted. At the end of each session, the session's time and errors were calculated. Based on these values, the experimenter decided whether the learner needed to conduct more training sessions or not.



Scale	Count	Percentage
1	45	38%
2	33	28%
3	23	19%
4	13	11%
5	5	4.2%
6	1	0.8%
7	0	0.0%

Fig. 10. The conditions' average evaluation distribution.

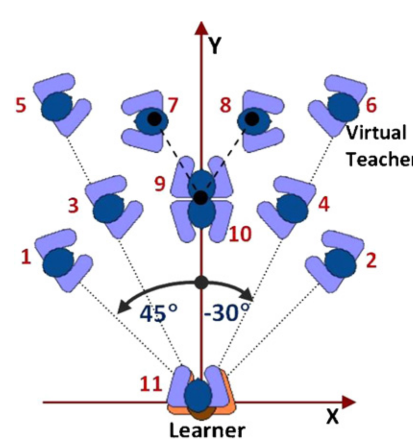


Fig. 11. The 11 evaluated conditions in the second experiment.

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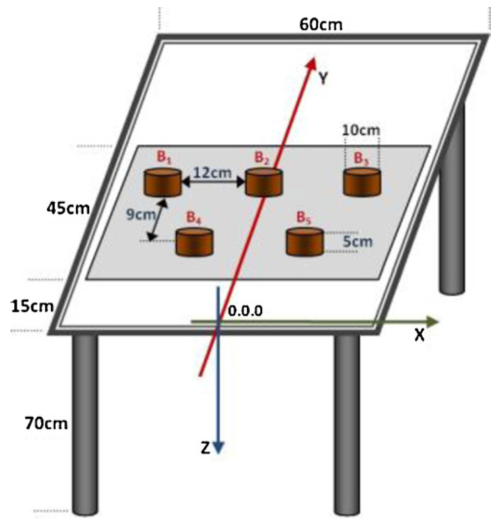

Fig. 12. The button distribution on the table.

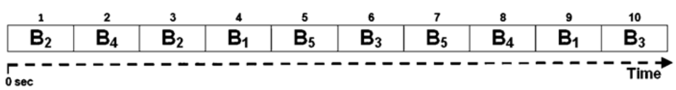

Fig. 13. Sample experimental physical task consisting of 10 motion units.

To commence this experiment, the learner put on the HMD, and put the markers on his/her hand. When the system started up, it displayed the 3D virtual teacher model in one condition randomly, superimposed on the physical space, as shown in Fig. 14. The experiment consisted of 11 sessions to evaluate the 11 conditions randomly. In each session one condition was evaluated. The learners were asked to complete the task of correctly mimicking the virtual teacher model's motion as quickly and accurately as possible. The virtual teacher demonstrated randomly one of the recorded physical task motion units in front of the learner. The learner took a rest for 15 s between the experimental sessions. The sessions were recorded on tape. Afterward, the sessions were reviewed and the task's error rate and accomplishment time were calculated for each condition. When the subject pushed a different button than the intended one, this was considered an error. The accomplishment time was measured from the start of each experimental session, until the subject successfully completed all the task's motion units.

4.2.5. Results

The training sessions' results showed that learners became accustomed to the system after an average of 4 sessions, where no significant changes in the task's accomplishment time, or the number of errors, were reported. Fig. 15 shows the average accomplishment time and average error rate per session.

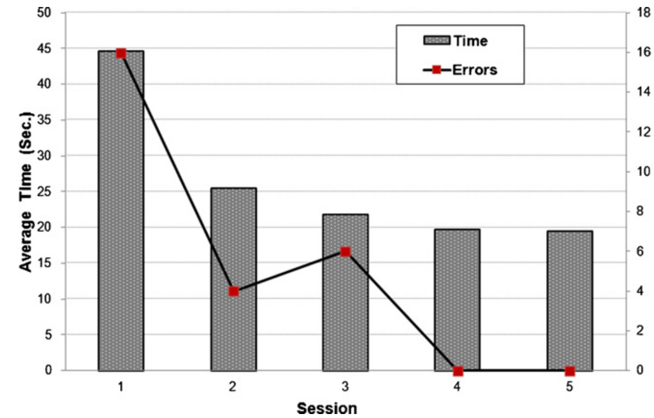

Fig. 15. The average accomplishment time and error rate per training session.

The experiment results show clearly that the virtual teacher's position and orientation have an effect on the learning outcome, both in terms of the required time to accomplish specific physical task learning, and in terms of the number of committed errors. Fig. 16 shows the average accomplishment time and error rate per condition.

Conditions 3 and 8 scored the lowest accomplishment time (mean = 15.1 s) and the lowest committed error rate (mean = 1.33%). To seek for any significant difference between the tested conditions we used the *t*-test comparison test. First, we ran the test over the opposite side conditions of 3 and 8. Comparing the results of conditions 3–4, we found no significant difference in the results [Time: ($t(14) = -1.3$, $p < 0.1$), Errors: ($t(14) = -1.1$, $p < 0.1$)]; and comparing conditions 8–7, we also found no significant difference [Time: ($t(14) = 0.7$, $p < 0.1$), Errors: ($t(14) = 1$, $p < 0.1$)]. Next we ran the test over conditions 9–11, with respect to condition 3. The results showed a significant difference between conditions 3 and 9 [Time: ($t(14) = -6.9$, $p < 0.001$), Errors: ($t(14) = -9.9$, $p < 0.001$)], between conditions 3 and 10 [Time: ($t(14) = -3.4$, $p < 0.01$), Errors: ($t(14) = -2.8$, $p < 0.05$)], and between conditions 3 and 11 [Time: ($t(14) = -2.9$, $p < 0.01$), Errors: ($t(14) = -1.2$, $p < 0.01$)].

5. Automatically adjusting the virtual teacher's rotation angle

In this section, we introduce a novel software 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

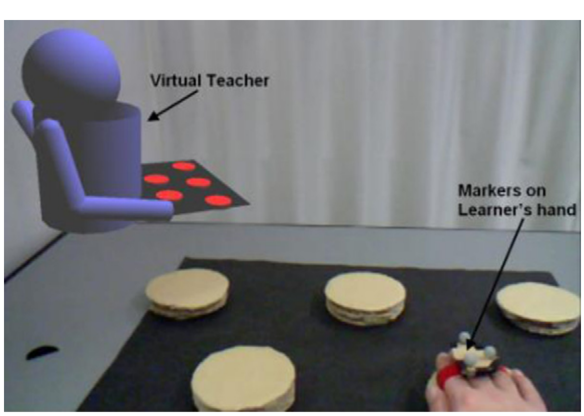

Fig. 14. The learner's view through HMD.

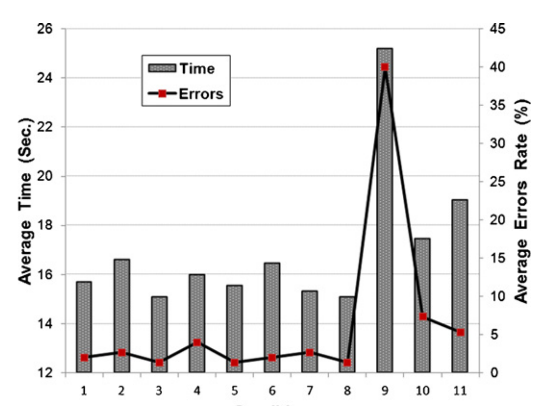

Fig. 16. The average accomplishment time and error rate per condition.

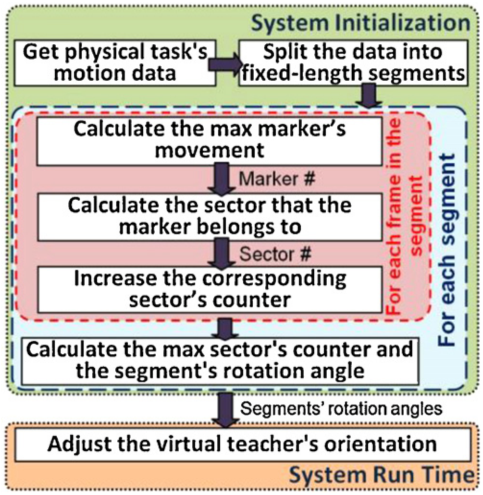

Fig. 17. The automatic adjustment processing flow chart.

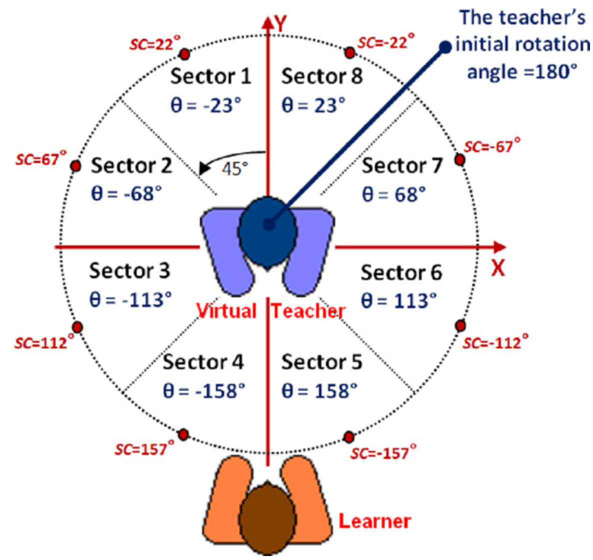

Fig. 18. The virtual teacher's environment divided into eight sectors.

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.

5.1. Automatic adjustment method design

The automatic adjustment processing flow chart is shown in Fig. 17. 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 are retrieved from a file system. Next, the task motion data are 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.

5.1.1. The virtual teacher's rotation angles

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 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 8 equal sectors as shown in Fig. 18. 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 sectors predefined rotation angle (θ) had been calculated so that the sector's center angle faces the learner when selected using the following equation:

$$\theta = 360 - \mathrm{SC}$$

where SC is the sector's center angle.

5.1.2. 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:

$$M_j = sqrt((X_{cj} - X_{pj})^2 + (Y_{cj} - Y_{pj})^2 + (Z_{cj} - Z_{pj})^2)$$

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 8 markers' absolute movement amounts, the maximum marker's movement MM_i is determined:

$$MM_i = \max(M_1, M_2, \ldots, M_8)$$

where i is the current frame number.

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

$$O_i = \arctan\left(\frac{Y_i}{X_i}\right)$$

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:

$$C_{\max} = \max(C_1, C_2, \ldots, C_8)$$

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).

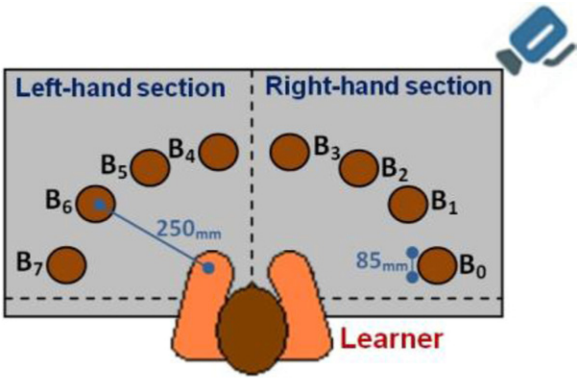

Fig. 19. The button distribution on the table.

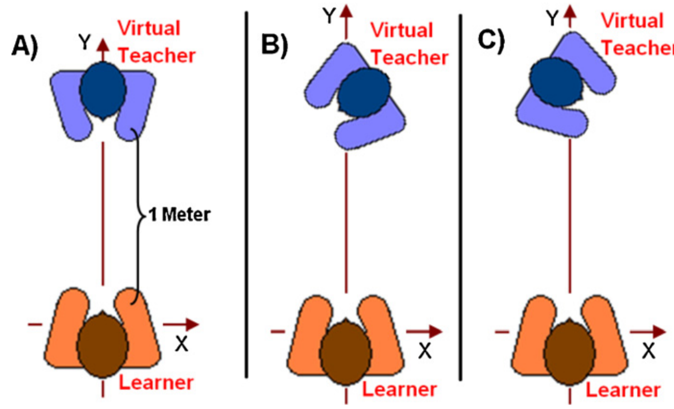

Fig. 21. The 3 fixed rotation-angle conditions: (A) 180°, (B) 105°, (C) −105° rotation angle.

5.2. Automatic adjustment experiment

To evaluate if the automatic adjustment method produces a better view, comparative generic physical-task learning experiment was conducted. The first part of this learning experiment was performed using 3 predefined and fixed virtual-teacher rotation angles. The second part was performed using the virtual teacher's automatic adjustment method. The experiments were videotaped and the error rates were compared and analyzed to find out any significant improvements between the conditions.

5.2.1. The physical-task learning platform

The physical-task learning platform we used to test the automatic adjustment method contains 8 buttons [B_0–B_7] placed on a table, as shown in Fig. 19. In order to engage the learner's both hands in the physical-task learning, 4 buttons [B_0–B_3] were operated by the learner's right hand, and 4 other buttons [B_4–B_7] were operated by the learner's left hand.

Since there were 8 buttons in this physical-task learning platform, 8 recording sessions were conducted to produce 8 unique sub-motion units; 4 sub-motion units were right-handed motions, and the remaining 4 sub-motion units were left-handed motions.

5.2.2. Producing physical-motion tasks

By using the 8 prepared basic sub-motion units, we systematically created a chain of sub-motions. A total of 40 sub-motion units were combined to create a one-motion task. This produced a movie of 44-s length (Fig. 20).

5.2.3. Participants

A total of 21 participants took part in this experiment as learners, 9 females and 12 males. Only two of those participants were participated in the previous experiments, while the rest were newly hired students. The participants' ages ranged from 20 to 33 (mean = 24, s.d. = 3.5), and they were mostly undergraduate or graduate 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.

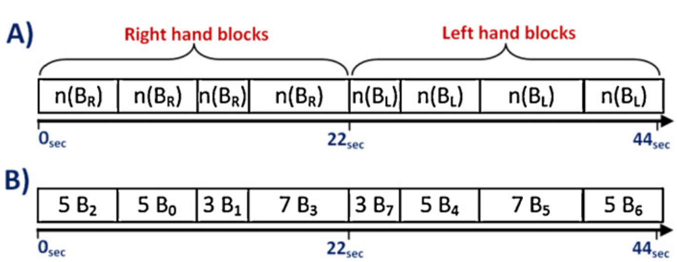

Fig. 20. (A) The motion task divided into eight blocks, where *n* represents the block size and has the value 3, 5, or 7. B_R is one of the right-handed sub-motion units, and B_L is one of the left-handed sub-motion units. (B) A sample motion task.

5.2.4. Fixed rotation conditions

Based on the result of our previous experiments, we decided to assess the top 3 fixed rotation-angle conditions (Fig. 21). The first condition has a 180° rotation angle, the second condition a 105° rotation angle, and the third a −105° rotation angle. In the three conditions, the virtual teacher was placed at 1 m virtual distance away from the learner. Fig. 22 shows the resulting virtual-teacher view in the 3 fixed rotation-angle conditions.

Each participant in this part of the experiment performed 3 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 3 fixed rotation-angle conditions, one by one. The virtual teacher continuously performed one of the pre-generated motion tasks for 44 s 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.

5.2.5. 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.

5.2.6. Results

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.

The fixed rotation-angle experiment's results are shown in Fig. 23. 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

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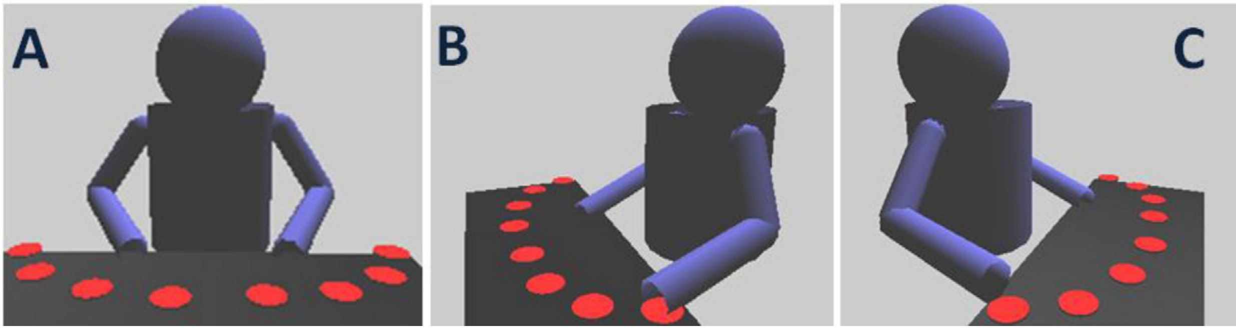

Fig. 22. The virtual teacher's appearance with: (A) 180°, (B) 105°, (C) −105° rotation angle.

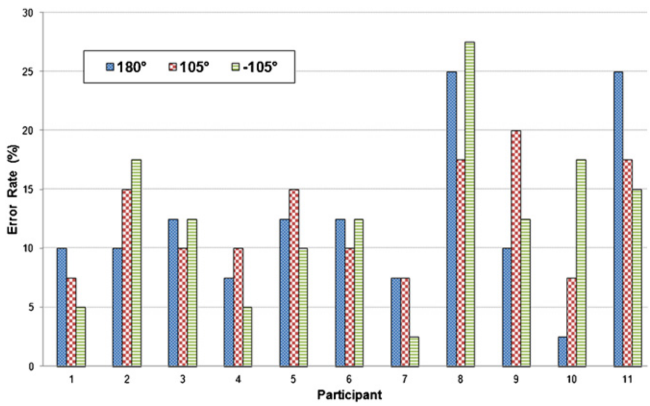

Fig. 23. The fixed rotation-angles' error rate per participant.

(−105°), 12.5% (s.d. = 7.1%). First, we tested the error rate's results of the 3 fixed rotation-angle conditions using ANOVA. The analysis confirmed no significant difference between the 3 conditions' average error rate ($F(2,30) = -0.0047$, $p < 0.01$). Therefore we summed up the 3 fixed-rotation conditions' data together to be used to compare with the automatic-adjustment condition's data.

On the other hand, Fig. 24 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 3 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. 25).

5.3. Adjusting the vertical view-angle

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. Accordingly the method only controlled the view's horizontal rotation angle. The vertical rotation and orthogonal view were not considered in the previous experiments. Therefore, a final experiment was conducted to find out the effect of adjusting the vertical viewing angle on observing a clear motion while mimicking a physical-task motion.

5.3.1. Experiment design

The physical-task learning system was updated so that the learner can manually set up the vertical view-angle, while the horizontal view-angle was adjusted automatically using our proposed method. To find out the relationship between the physical motion with respect to the vertical view angle, 4 distinct motions were prepared in advance as follows:

- 1-Sector physical-task motion: in this motion the virtual teacher used his hand over one sector.
- 2-Sectors physical-task motion: in this motion the virtual teacher used his hands over 2 sectors.
- 3-Sectors physical-task motion: in this motion the virtual teacher used his hands over 3 sectors.
- 4-Sectors physical-task motion: in this motion the virtual teacher used his hands over 4 sectors.

The participants in this experiment were asked to mimic the virtual teacher's physical motion. The vertical viewing angle was manually adjusted by the participants themselves to the degree

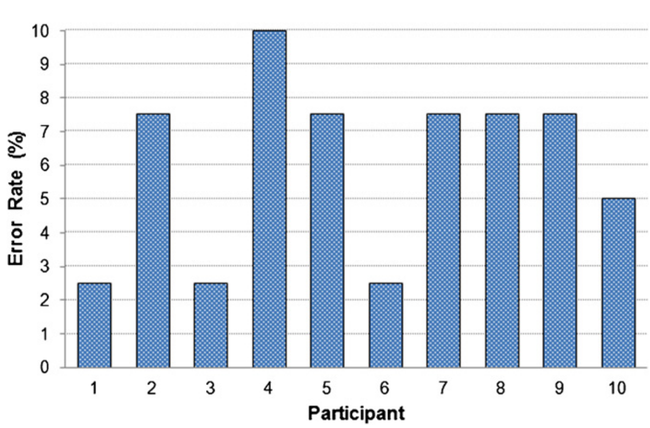

Fig. 24. The automatic adjustment's error rate per participant.

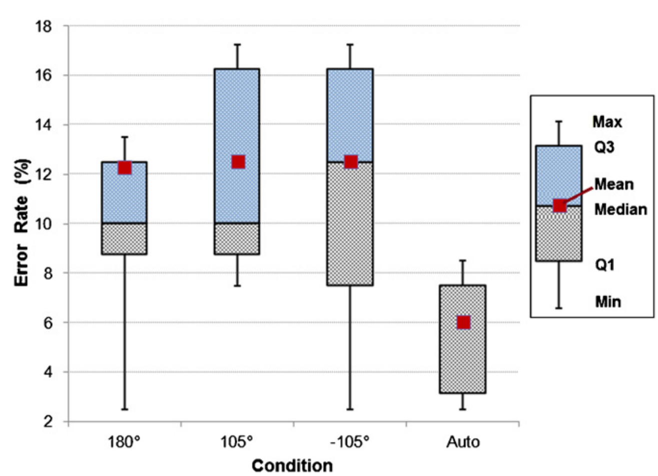

Fig. 25. The average error rate per condition.

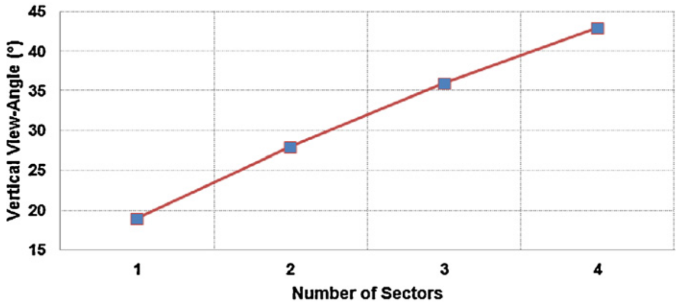

Fig. 26. The average vertical view-angle per the number of sectors.

that he/she felt more comfortable and the motion is the most clear. The vertical adjusting value ranged from 0° to 90°. 0° vertical view-angle represents the normal situation where the virtual teacher placed in front of the learner at the same horizontal sight level, while 90° vertical view-angle represents the orthogonal view situation.

5.3.2. Participants

A total of 5 participants were hired to participate in this experiment, 2 females and 3 males. All the participants were right-handed and had normal or corrected to normal vision.

5.3.3. Results

Fig. 26 shows the average resulted vertical view-angle per the number of sectors. For 1-sector motion, the participants sit the vertical view-angle to 19°; for 2-sectors motion, a 28° was selected; for 3-sectors motion, a 36° was chose; finally for 4-sectors motion, a 43° was best.

6. Discussion

Physical-task learning in mixed-reality environments becomes very popular in wide areas as seen in Section 2. Without doubt, this training technique could become the first option in many domains if it designed well. The virtual teacher's setup is one important aspect to achieve an effective training system. Many implemented training systems had considered a fixed and limited virtual teacher's location(s) and rotation(s) (Yang and Kim, 2002; Nakamura et al., 2003; Chua et al., 2003; Patel et al., 2006; Kimura et al., 2007). In contrast, we thoroughly investigated the virtual teacher's location and rotations and there effects on the sample physical-task learning.

The first experiment aimed to identify the ranges of the virtual teacher's location and rotation most comfortable and instructive for the learner. The result shows that learner preferred front side-view of virtual teacher. Despite the small sample-size, the participants' preference results were very consistent. This general result was expected as learner preferred to see the physical objects and virtual teacher before him/her in his/her spatial environment. This might be the reason why many of the implemented training systems had employed a virtual teacher in front of the learner such as (Patel et al., 2006; Nakamura et al., 2003; Komura et al., 2006; Miyawaki and Sano, 2008; Chan et al., 2007).

The second experiment's result verified that looking at the virtual teacher model from the side decreases both the time and the error rate, and looking at the virtual teacher's model from behind or in front increases the time and error rate significantly. Regarding condition 9, the hand motion was completely or partially hidden by the virtual teacher's body. Regarding condition 10, the opposite-hand view caused the learner to consume more time and commit more errors. A final interesting point: we found that conditions 1, 3, 5, and 8 scored better results, in comparison with conditions 2, 4, 6, and 7, even though all of these conditions represented a form of side-view. This is because our experiment's physical motion task was recorded using the right hand only, meaning that the physical motion was more visible from the right side-view.

For physical motion task where the virtual teacher uses both hands, or rotates around, the proposed automatic adjustment method turned to be more effective compared with fixed rotation conditions. The experiment result shows that the automatic adjustment method significantly decreased the average error rate. 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 with the wrong hand.
- Type C error: When the total number of the 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.

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 often 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 true 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.

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 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 both the buttons from the far ends (B_0 and B_7), the minority suffered a bad view because the method gives the majority a good view.

Our proposed method assumed that the learner will sit and see the virtual teacher in front of her/him at the same horizontal sight level as if a real situation. The method only controls the view's horizontal rotation angle. The vertical rotation and orthogonal view were investigated in this study as well. From the experiment of adjusting the vertical view-angle's result, we can conclude that the more sectors involved in the physical-tasks motion the more vertical view angles are wanted to see the whole motion clear. 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; 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.

The current research has other limitations such as the chosen simple push-button physical task as a learning model. This task is considered simple to perform, because the learner needs only to move his/her hand and push one of the buttons. The learner's body motion itself was not considered as long as the target button was correct. However, a real-life physical task (e.g., cooking task, sport task, dance task, etc.) might be better to accurately evaluate the proposed method. Next, the sample size is considered small which makes the generalization difficult. Even though the result shows significant differences; a larger balanced sample size is required to robustly adopt the results. This study did not deal with the gender and/or age differences, so the result obtained in this study might be limited to relatively young males. Taking those gender and age differences into account can be a future study issue. Finally, the 3D virtual teacher's avatar was implemented using plain cylindrical model to minimize any effect of the virtual teacher model's appearance. However, the virtual teacher's shadows were not implemented at this stage. The effect of the shadows has been found very important in the 3D feelings (Hamalainen et al., 2005) and without them the motion and the distance might be falsely interpreted. Accordingly, shadows have to be considered in any future implementation.

7. Conclusions

In this study, we first investigated physical-task learning when mimicking a virtual teacher's motion in a mixed reality environment. More specifically, we investigated the virtual teacher's optimal position and rotation for the best learning outcomes. These outcomes were measured in terms of the required time to accomplish the physical task and the number of committed errors.

To this end, a physical-task learning support system was developed, which had the flexibility to relocate the displayed virtual teacher by changing the virtual teacher's distance, shifting angle, and rotation angle (manually and automatically). Also, the system had the ability to provide real-time feedback notification by capturing the learner's motion. This feedback was used to determine whether the learner performed a motion unit task correctly or not.

The virtual teacher's optimal position and rotation investigation involved two experiments. The first, preliminary experiment was conducted to narrow down the wide range of possible virtual teacher positions and rotations; and based on its results; the second experiment was conducted to determine the optimal virtual teacher position and rotation for the best learning outcome. The experimental results suggest that the 3D virtual teacher's close side-view is the optimal view for such physical-task learning (which includes one-hand movement), and that displaying a semi-transparent virtual teacher has no significant effect on the results.

Afterward we proposed a software 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, comparative 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 a 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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