Helping physical task learning by automatic adjustment of a virtual teacher's rotation angle

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2 authors, including:

Mamoun Nawahdah
Birzeit University

Helping Physical Task Learning by Automatic Adjustment of a Virtual Teacher's Rotation Angle

Mamoun **NAWAHDAH** and Tomoo **INOUE**
Graduate School of Library, Information and Media Studies
University of Tsukuba
Tsukuba, Japan
{nawahdah, inoue}@slis.tsukuba.ac.jp

Abstract— **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 of the virtual teacher's rotation angle, so that the learner can observe the important body motion easily. The method divides the whole task motion into fixed duration segments, seeks the most moving part of the body in each segment, and rotates the virtual teacher to show the most important part to the learner accordingly.**

To test the method, a generic physical task learning experiments have been conducted. The method was revealed to be effective to the motion that gradually changes the most moving part such as manufacturing and cooking tasks.

Virtual Reality; Mixed Reality; Physical Task Learning; Human Computer Interaction

I. 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[1]. Finally, MR use enhances users' perception of, and improves their intuitive interaction with, the real world[2].

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, using sensors and virtual reality[3][4]. The results suggest that MR is suitable for supporting physical task learning. Thus, we have developed a physical task learning support-system using MR[5]. The system visualizes a real-world 3D virtual teacher model in front of the learner.

It has been shown in previous research that a virtual teacher-model's position and rotation angle have significant effects on learning[5]. The results show that the virtual teacher's 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 moves around, 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, and more specifically on his/her body movements. The purpose of this method is to ensure that the virtual teacher's most moved body part is visible to the learner. This will enhance the learning outcome, and the learner will feel more comfortable and assured during learning. The outcome was measured in terms of the number of committed errors.

A generic physical task learning experiments have been conducted to evaluate the method, comparing to normal fixed virtual teacher's rotation conditions. The experiment's results shows that using the automatic adjustment method did significantly decrease the number of committed errors.

II. 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[6][7][8][9][10]. Some of these systems enhance the learning experience by virtually displaying related information and providing necessary feedback; and such systems have proven useful in various domains.

Horie *et al.*, for example, proposed an interactive learning system for cooking in an MR environment, using video data extracted from TV cooking programs[11]. 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 performing actions corresponding to the current cooking step is displayed in a fixed location at a table as well[12].

Regarding dance skills acquisition, Chu *et al.* proposed a wireless virtual reality system for teaching Chinese 'Tai Chi'[10]. 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 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[13].

The results confirmed that the superimposed method is the most effective for repetition of partial movements, while the others are effective for whole 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, the ability to sense the learning task and its progress is built in to virtual reality-based learning support systems[3][14][7]. 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[3]. Such motion-capture technology is used in a dancing training system developed by Chan *et al.* [15]. 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 displayed 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[16]. The learner wears a motion-capture suit and HMD. The virtual teacher appears, alone, in front of the user, through the HMD. The virtual teacher location and rotation angle is 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[17]. 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 multi surrounding display to help the dancers conveniently view from arbitrary angle. In another study, Krik *et al.* demonstrated how remote gestures influence the structure of collaborative discourse[18]. The results suggest that the use of remote gesture technologies does indeed 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 move or control the projected view.

On the other hand, our system focuses on a specific point on presenting the virtual teacher, which is the optimum rotation angle that leads to the optimum result. Fixing the teacher's rotation angle will not leads to such result. Thus, our study can be considered a further enhancement to other learning systems.

III. 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 Figure 1. Six NaturalPoint Optitrack™ (FLEX:V100) optical motion-tracking cameras are placed above a table. The cameras resolution is 640x480pixels, and the view angle is 45° field of view (FOV). These cameras are used to detect the learner's motion by tracking visible reflective markers that are placed on the learner's body. The reflective markers are placed on the learner's hands. In our system, the position and orientation of each marker can be measured with an accuracy of 2mm[1].

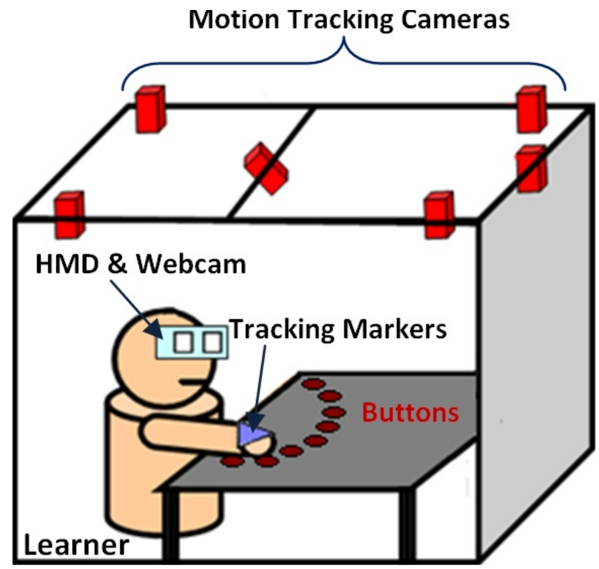

Figure 1. The physical workspace of the physical task learning support system.

The physical task learning platform contains eight buttons [B_0-B_7] of 9cm in diameter and 1cm in height, placed on a table, as seen in Figure 2. The distance between the buttons and the learner's hands are fixed to 25cm. The buttons were arranged in this way, so that the physical motions are distributed over the learner's entire front space. The buttons [B_0-B_3] will be operated by the learner's right hand, while the buttons [B_4-B_7] will be operated by the learner's left hand. This generates the kind of motions that cover a wide range of real physical tasks.

To minimize any effects of the virtual teacher model's appearance on the task performance, a plain cylindrical 3D virtual teacher model was used in the study, as shown in Figure 3. The 3D model is presented to the learner by a HMD (VUZIX® iWear VR920). The used HMD resolution is 640x480pixels, weights 90g, and the view angle is 32° FOV.

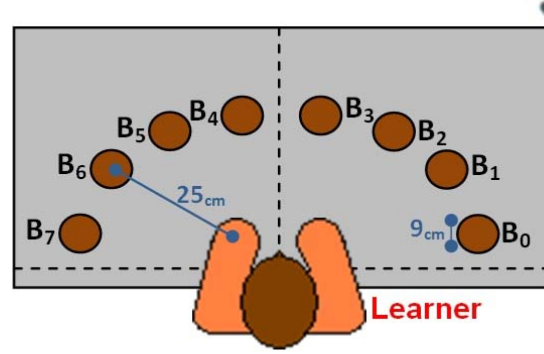

Figure 2. The button distribution on the table.

[1] http://www.naturalpoint.com/optitrack/products/flex-v100r2/features.html

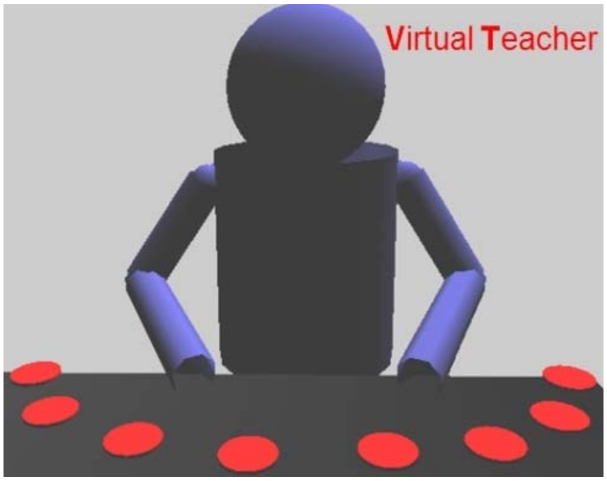

Figure 3. The 3D virtual teacher's appearance.

A program has been developed to render the learner's mixed-reality scene, which is the combination of the real scene and the generated 3D virtual teacher model. The real scene is captured by a small iWear CamAR® camera clipped-on the VR920 HMD. While the virtual teacher performs the physical task, the program receives motion data from the motion-capture cameras, and decides whether the learner's action is correct or not.

IV. MAVT System Implementation

The automatic adjustment processing flow is shown in Figure 4. The system is divided into two main processes: initialization process and run time process. During the system initialization, the virtual teacher's motion data is retrieved from a specific motion data file. Next, the motion data is split into small fixed-duration segments. For each motion segment, the teacher's optimum rotation angle is calculated. During system run time, the teacher's motion data is split into segments and displayed. Before displaying each segment, the teacher's rotation angle is automatically adjusted, according to a pre-calculated optimum rotation angle, so the main teacher's movement is facing the viewer.

A. Preparing Physical Task's Motion Data

Sub-motion units, which show the virtual teacher pushing one of the 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 motion. To capture the real teacher's motion while performing the motion units, eight unique reflective markers were placed on the teacher's body, as shown in Figure 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 I shows a sample motion captured data. Each line in the motion data file represents one frame of motion data, and each frame contains the eight markers' positions data. These motion data are used to determine the most moving marker in each frame relatively to the previous frame makers' positions. The sub-motion unit's duration is 1.1 seconds on average. Since there were eight buttons, eight recording sessions were conducted, to produce eight sub-motion units.

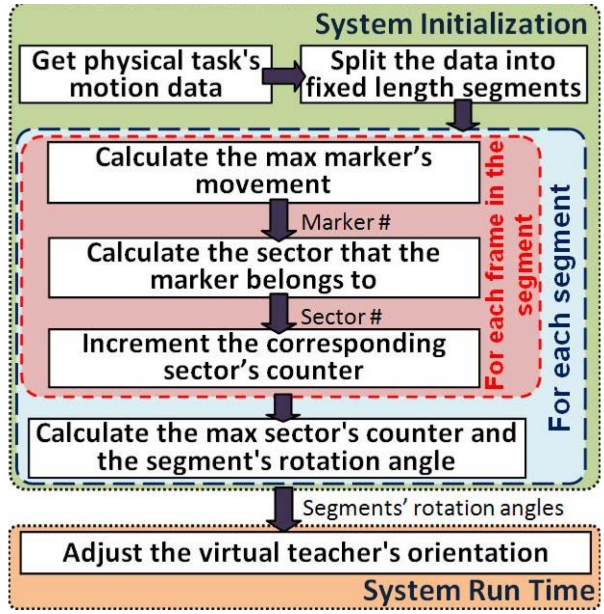

Figure 4. The automatic adjustment processing flow.

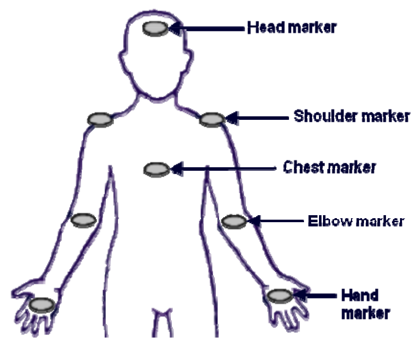

Figure 5. The marker locations on the teacher's body.

TABLE I. SAMPLE MOTION CAPTURE DATA.

Frame #	Head			Chest			Right Shoulder		
	X	Y	Z	X	Y	Z	X	Y	Z
0	0.01	1.81	-0.33	-0.04	0.26	-0.41	0.51	0.95	-0.67
1	0.01	1.82	-0.34	-0.03	0.26	-0.40	0.51	0.95	-0.67
2	0.01	1.81	-0.33	-0.03	0.26	-0.40	0.51	0.95	-0.68
3	0.02	1.81	-0.33	-0.03	0.26	-0.40	0.51	0.95	-0.68
4	0.02	1.81	-0.33	-0.03	0.26	-0.40	0.51	0.95	-0.68

B. Virtual Teacher's Rotation Angles

The virtual teacher's surrounding area is divided into eight equal sectors as shown in Figure 6. Each sector covers 45° rotation range, and each has an associated counter (C_1-C_8). These counters are used to hold the count of the virtual teacher's maximum moved marker in each sector during the automatic adjustment process. The sector with the maximum counter's value is considered the sector that contains the most important movements. Accordingly, the virtual teacher's rotation angle will be rotated to the sector's predefined angle (**θ**). The sector's rotation angle (**θ**) is calculated by the following equation:

$$\Theta = 180° + (180° - SC) \quad (1)$$

Where SC is the sector's center angle.

The sector's predefined angle (θ) is calculated so that the sector's side-view faces the learner when selected.

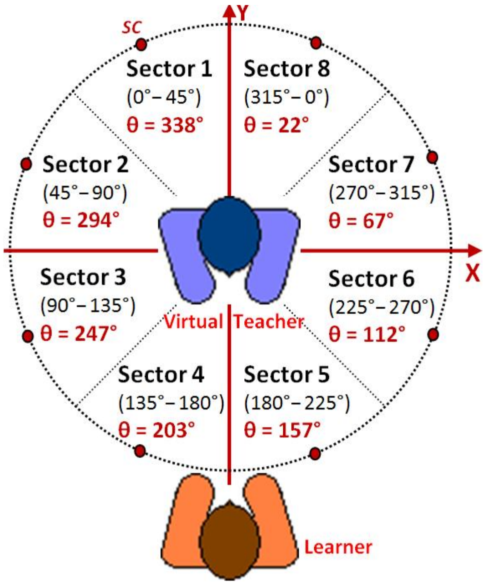

Figure 6. The teacher's surrounding area divided into eight sectors.

C. Calculating the Segment's Adjustment Orientation Angle

This process starts by reading the segment's motion data frame by frame. For each marker's coordinate data in the frame, the absolute marker's movement amount M_j is calculated based on the previous frame's data:

$$M_j = \sqrt{(X_c - X_p)^2 + (Y_c - Y_p)^2 + (Z_c - Z_p)^2} \quad (2)$$

Where j is the marker number ranged from 1 to 8. X_c, Y_c, and Z_c are the current frame marker's position. X_p, Y_p, and Z_p are the previous frame marker's position.

Next, the maximum marker's movement MM_i is determined:

$$MM_i = Max(M_1, M_2, \dots, M_8) \quad (3)$$

Where i is the current frame number.

For this marker, which has the maximum movement, we calculate the angle O_i:

$$O_i = Arctan(\frac{Y_i}{X_i}) \quad (4)$$

Based on the calculated O_i, the associated teacher surrounding sector's counter will be increased by 1. Once all the segment's frames are processed the same way, the max sectors' counter value C_{max} is determined:

$$C_{max} = Max(C_1, C_2, \dots, C_8) \quad (5)$$

This sector is assumed to be that wherein the most important motion has occurred. Accordingly, the segment's rotation angle (SO) will be set according to this sector's predefined angle (θ).

V. MAVT EXPERIMENTS

To prove that the automatic adjustment method will produce a better view; two physical task learning experiments were conducted. The first learning experiment performed using three predefined fixed teacher's rotation angles. The second learning experiment performed using the teacher's automatic adjustment method. The results were analyzed to find out any significant deference between the two experiments.

A. Participants

A total of 21 participants took part in these experiments, 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 experiment, and the other group performed the second experiment. 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.

B. Training Sessions

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.

The training session's task consists of 10 random motion units. Each motion unit consists of pushing one of the eight buttons. The learners were asked to correctly copy the virtual teacher's motions. The virtual teacher performed one motion unit and waits until the learner perform the same motion. When the learner correctly performs the same motion, the system displays the next motion unit.

The training sessions' results showed that learners became accustomed to the system after an average of 5 sessions, where no significant changes in the task's accomplishment time, or the number of errors, were reported.

C. Motion Task

In order to test the automatic adjustment method, a distinctive set of motion tasks has been constructed. By using the sub-motion units, we built a chain of sub-motions. A total of 40 sub-motion units were joined together to construct a block of motions. The block of motion's duration is about 44 seconds. To avoid distracting the viewer, we split the block of motions to 8 sub-blocks, where the first 4 sub-blocks are right handed motions, and the last 4 sub-blocks are left handed motions (see Figure 7). To assure that the learner will not memorize the number of motions within each sub-block, we used variable sub-block size of (3, 5, or 7).

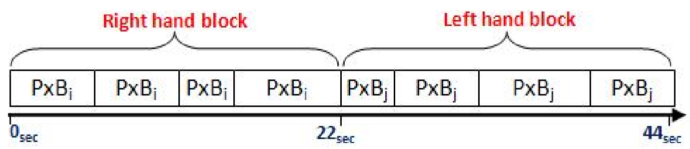

Figure 7. Motion task divided into eight sub-blocks. Where, **P** has the value 3, 5, or 7. $\mathbf{B_i}$ is the button number ranged from 0 to 3. $\mathbf{B_j}$ is the button number ranged from 4 to 7.

D. *Fixed Rotation Experiment*

It has been shown in previous research that a virtual teacher-model's position and rotation angle have significant effects on learning[5]. The results show that the virtual teacher's side-view is the optimal view for physical task learning that involves one hand motion. Based on this, we decided to experiment the resulted top three rotation conditions from our previous study (see Figure 8). The first condition has **180°** rotation angle, the second condition has **105°** rotation angle, and the third condition has **-105°** rotation angle. In the three conditions, the virtual teacher was placed at 1 meter virtual distance from the learner. The subjects were asked to concurrently copy the teacher's motion task.

E. *Automatic Adjustment Experiment*

In this experiment, the virtual teacher was placed at 1 meter virtual distance from the learner. The virtual teacher's rotation angle was automatically adjusted during run time. The participants were asked to concurrently copy the teacher's motion.

VI. RESULTS

Each experiment's session last for 44 seconds. The sessions were recorded on tape. Afterward, the sessions were reviewed and the task's error rate was calculated for each condition. When the subject pushed a different button than the intended one, this was considered an error.

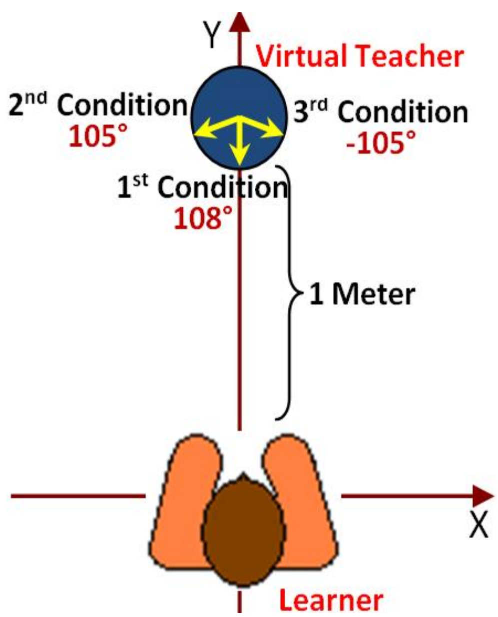

Figure 8. The three conditions used in the fixed rotation experiment.

Our goal is to prove that the automatic adjustment method will minimize the number of errors by providing a better view. This assumed to improve the physical task learning. The results of the two experimented groups have been analyzed to find out whether using the automatic adjustment method is significantly reduces the number of errors or not.

A. *Fixed Rotation Experiment's Results*

The error rate per participant in each condition is shown in Figure 9. The average error rate is calculated to be: for the first condition is 12.27% (s.d.=6.9%), for the second condition is 12.5% (s.d.=4.6%), and for the third condition is 12.5% (s.d.=7%). This results shows no significant difference between the first condition and the second condition ($t(11)=-0.14$, $p<0.05$). Also, the results shows no significant difference between the first condition and the third condition ($t(11)=-0.11$, $p<0.05$).

B. *Automatic Adjustment Experiment's Results*

The error rate per participant is show in Figure 10. The average error rate is calculated to be 5.4% (s.d.=2.46%).

C. *Fixed Rotation vs. Automatic Method*

Comparing the results of the automatic adjustment method with other group's conditions, we found that the automatic method scored less error rate and it's significantly different (see Figure 11). Comparing the automatic method results with the first condition shows a significant difference ($t(5)=2.9$, $p<0.05$). Comparing the automatic method results with the second condition shows a significant difference ($t(5)=3.5$, $p<0.05$). Finally, comparing the automatic method results with the third condition shows a significant difference ($t(5)=1.9$, $p<0.1$).

VII. CONCLUSION

In this paper, we propose a method for the automatic adjustment of a virtual teacher's rotation angle, when the virtual teacher is demonstrating physical task motion. This method will ensure that the learner sees the teacher's motion from an optimal viewing angle.

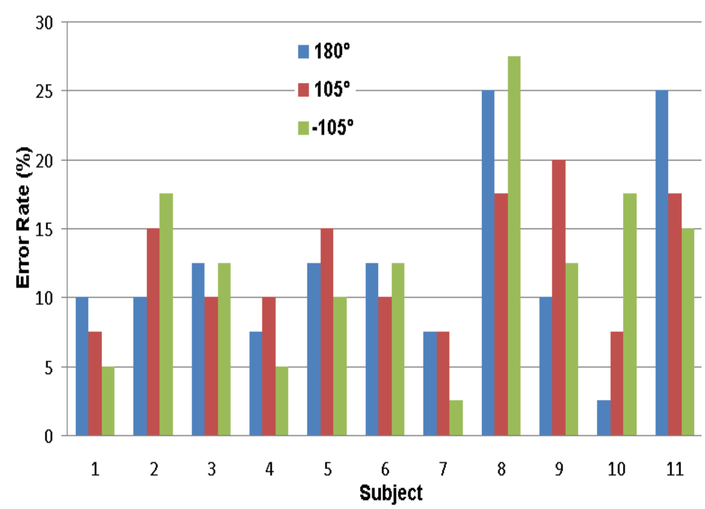

Figure 9. The Fixed Rotation Experiment's Results: Error rate per participant

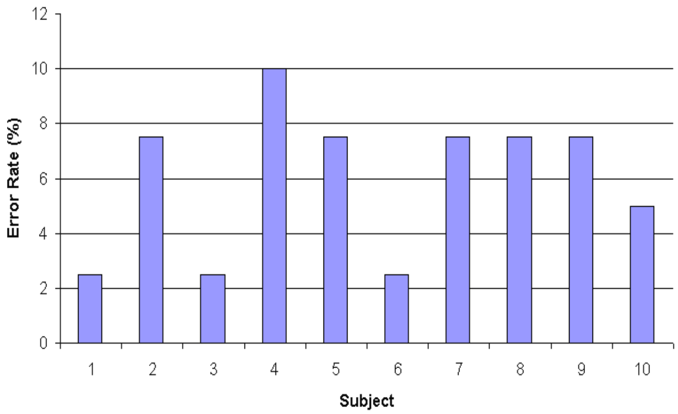

Figure 10. The Automatic Adjustment Experiment's Results: Error rate per participant

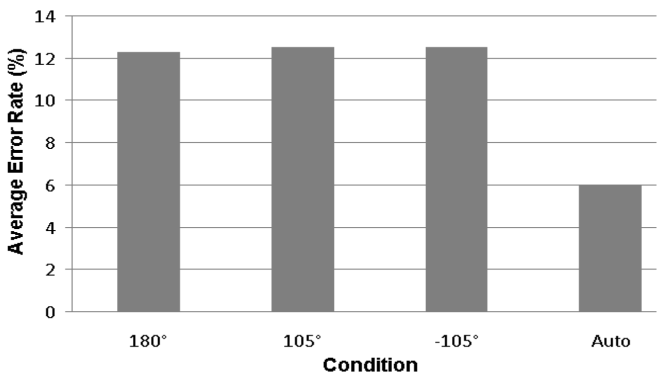

Figure 11. Fixed Rotation vs. Automatic method's Results: Average error rate per condition

To prove that the automatic adjustment method will produce a better view; two physical task learning experiments were conducted. The first learning experiment performed using 3 predefined fixed teacher's rotation angles. The second learning experiment performed using the teacher's automatic adjustment method. The result shows that the automatic method scored less error rate comparing to fixed teacher's rotation angle.

Such a 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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