Evaluation of Response Models to a Series of Commands in a Telerobotics Supervisory Control System

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Abstract. In contrast to direct manual control of manipulators, telerobotic interaction based on human supervisory control allows human operators to plan the movement of the remote machine by entering a series of commands as pre-defined positions. There are two possible kinds of response movements from executing this series of commands. Firstly, the robot moves towards the newly defined position immediately; or, secondly, the robot moves to achieve all the queued series of positions one by one. This paper describes an experiment to test the performance of the two kinds of response movements under varying visual feedback scenarios. By applying a mixed reality environment as the telerobotics interface, this experiment makes use of virtual objects to provide additional information for planning and monitoring the process. The highest productivity was achieved using a queue based model of interaction with additional visual cues. This was also compared to direct manual control and found to be considerably superior.

Keywords: Human Supervisory Control, Telerobotics, Multi-defined position, Response Movement, Virtual Information.

1 Introduction

The advancement of telerobotics technology allows a move from manual operation to full automation. This transformation can reduce human workload and increase productivity. However, unlike factory or industrial areas which utilise machines to perform a repeatable task [1], in mining areas most scenarios are varied and require human operators to make decisions in performing the task. Therefore, direct manual control is most commonly applied in mining areas.

Human supervisory control is proposed to shift the control model toward automation without eliminating the role of the human operator in the operating process. This technology is an alternative to manual operation that minimises human operator involvement without interfering with the machine performance [2][3]. Supervisory control systems are used by a human operator who acts as the supervisor of the intelligent system, which allows them to plan, monitor and intervene in the process when needed.

In telerobotics with supervisory control, the human operator can define a series of input commands, which will be carried out automatically by the machine. There are

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two possible response movements namely "Adaptation" and "Queue". In general, the Adaptation model works by moving the manipulator immediately to a new position. The Queue model works by making sure the manipulator reaches all intermediate positions one by one before reaching the final position.

Another important aspect in telerobotics is the ability of the interface (system) to provide information on the remote location to the end user. From previous work[4][5], we developed a telerobotics user interface by utilising a mixed reality environment that integrates information between a 3D virtual environment and a live video. The advantage of using the virtual environment is the ability to create a number of virtual objects to provide visual feedback information, which is useful in planning, monitoring and performing the task.

This paper describes an experiment that was conducted to test a telerobotics system utilising human supervisory control based on response movements from a series of input commands in a mixed reality interface. The key questions of the experiment were:

a. Based on the completion time and success rate, how do the performance of the Adaptation and Queue models compare?
b. Could the visual planning information improve the operator performance in task completion?
c. Would the human supervisory control model be able to replace manual/direct control for this experiment design task?

The rest of this paper describes related works on human supervisory control (section 2); the introduction of two models of response movement (section 3); the prototype implementation of our telerobotics system (section 4); the evaluation of the experiment (section 5) and the experimental results (section 6). The paper is concluded with a discussion of the results (section 7 and 8).

2 Related Work

The term supervisory control (SC) has emerged in most areas of the industry, from auto-pilot [6] to smart-phones [7][8]. In general, human supervisory control can be defined as an interaction between a human, who acts as the supervisor, and the machine/system, which acts as the subordinate. Tendick [9] said that human supervisory control is a system where a human operator acts as a supervisor who has the abilities to plan, monitor and interrupt the process during the execution carried out by machines. In telerobotics, human supervisory control can also be a preference to direct/manual control[1–3]. Human supervisory control has a number of advantages such as the ability to improve the reliability of the machine's performance without total human involvement [1]; simplify the control process by defining movements and goals rather than fully controling the process; minimise the effect of time delay in communication between human and teleoperator [3][10][11]; and eliminate the requirement for continual human attention, therefore reducing the operator workload.

Based on its definition, human supervisory control has three generic supervisory functions, which are known as planning, monitoring and intervening (interrupting).

Sheridan [1] states that the important aspect in telerobotics supervisory control is the ability of the system (computer) to package consolidated information in a visual display to the human operator. This information is useful for planning and examining the task performance and for making a quick decision to override the process when needed.

3 The Model of Response Movement

The experiment was a continuation of our previous work in telerobotics using a Mixed Reality Interface [4][5]. We conducted the experiment by testing human supervisory control as an alternative input model to direct/manual control. As mentioned above, human supervisory control allows the human operator to input a series of commands when defining target positions. In this experiment, we grouped the possible kinds of response movements into two models as follows:

a. Adaption Model

This response model has the ability to respond to the operator's commands by moving to a new position immediately. The algorithm in the adaptation model forced the 3D model or the manipulator to cancel the current process, update its target according to the new position determined, and continue the process towards the new target. This model gives human operators more control in supervising the manipulator's movement.

b. Queue Model

This response model adopts the logic of queuing services. The queuing services works by following a FIFO (First-In-First-Out) concept where the system needs to complete servicing one entity before continuing to the next entity. This system is shown in Fig.1 where the 3D model or the manipulator moves to reach all the positions one by one.

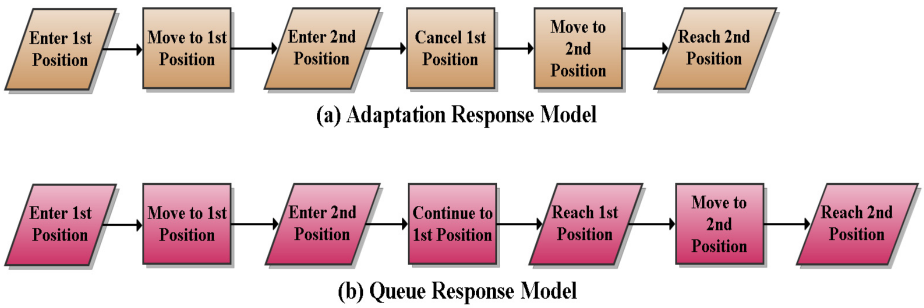

Fig. 1. Diagram of Adaptation and Queue response model

4 Prototype Implementation

We built a closed loop client server communication between the operator–interface (as client) and the server/remote machine (as manipulator). The overall system is illustrated in Fig.2.

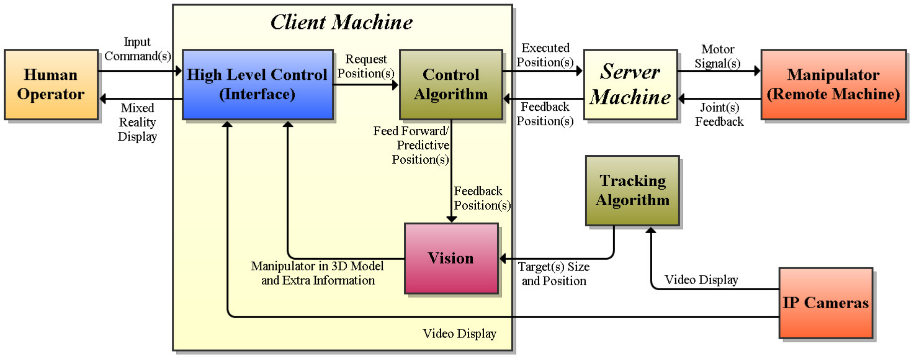

Fig. 2. Diagram Telerobotics System Implementation (Overall System)

4.1 Our Telerobotics System

We developed an interface using a gaming engine called unity3D for user interaction. A 3D model of a robot arm was inserted into this virtual environment to show the real time position feedback from the robot arm. In applying the mixed reality concept and provide all information in a single screen, we also added video streaming from the IP camera which was installed at the remote location. At the remote location a server was built to convey any information between the robot arm and the end user. Further, the server is also connected to the IP camera to track the positions of the target objects (blocks) and update these positions on the end user interface.

4.2 Features Available

Our user interface provided all the information, including the previous information (feedback), current information (monitoring) and future information (planning). In the unpredictable situation where the manipulator is stuck before reaching the target positions or where the human operator needs to change/cancel the robot's movement, they can override the process instantly. There are a number of features available on this system to enhance the performance of human supervisory control.

a. Stop Functions

In emergency situations, the system provides a number of functions that can be used to override the current process and take control of the movement. These functions are temporary stop (TS) and full stop (FS). Firstly, the temporary stop (TS) is a function which works by suspending the predicted model and robot's movement temporarily by holding a key button, and allowing them to continue moving to the target when the operator releases the button. This function allows the operator to suspend movement while they evaluate the situation. Secondly, the full stop (FS) function works by stopping the robot's movement and at the same time cancelling all subsequent targets.

b. Path Finding Algorithm

Our user interface represents detected block as 3D models each of which can be defined as a target block. However, it was designed so that only one block can be selected as a target object. When a model block is selected as a target, the remaining blocks will serve as obstacles to the manipulator. Accordingly, a function is added into the system, which is adopted from A*(read: A-star) path-finding algorithm, to create paths which allow the robot to avoid the obstacles automatically.

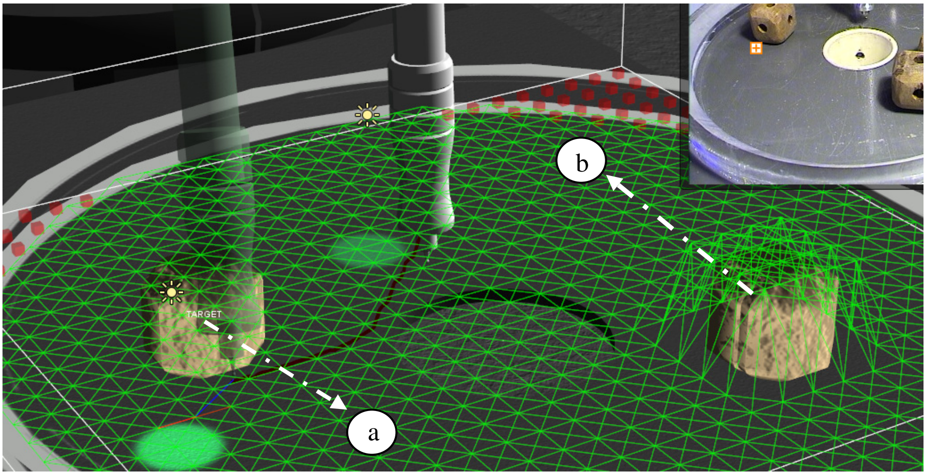

Fig. 3. Path generating from A*(A-star) algorithm in (a) selected block and (b) unselected block model

c. Visual Planning Information

A mixed reality concept combines information gained from the virtual environment and live video [4][5]. The telerobotics user interface allows the computer to provide virtual objects as prediction or feedback information. These virtual objects can be utilised for planning, monitoring and intervening in processes. Below are four examples of the virtual objects which have been used (See Fig.4).

A "green circle" object serves as planning information to help the operator by showing the series of target positions. It appears when a target position for the robot is defined. Each green circle had a diameter of 4mm indicating that the error tolerance for the model/robot to reach the destination target was 0 – 2mm. Another virtual object that was used is the "shadow TIP". It gave a prediction of the position of the

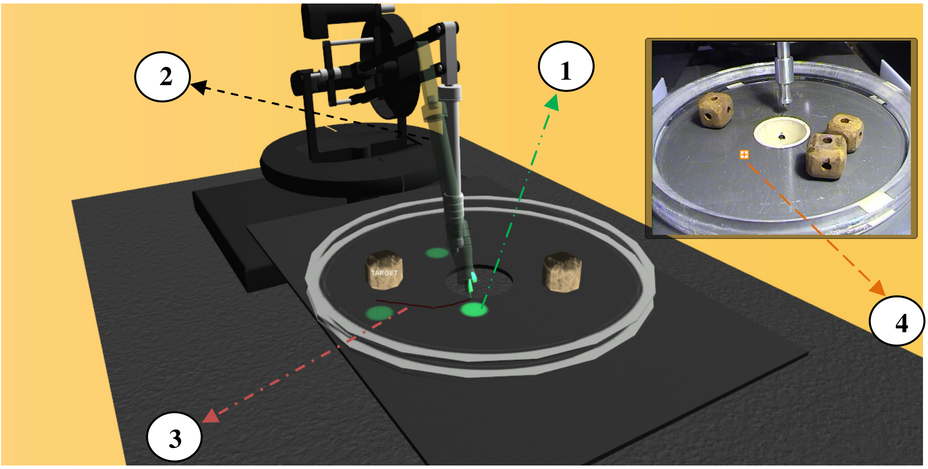

Fig. 4. Visual informations (1) Green circles. (2) Shadow TIP, (3) Line path, and (4) Overlay pointer.

manipulator model and replicated the shape of the robot arm TIP model by using a transparent texture. The “line path” was another virtual object. This line pointed towards the TIP shadow object to predict the path of the manipulator model. The last virtual object is the “overlay pointer”. It was presented as a cross symbol and showed the predicted position of the TIP on the video display. The overlay pointer applied the concept of augmented reality by enhancing virtual object overlays on the live video.

In order to analyse the performance of this visual planning information, each response movement model (Adaptation and Queue) was tested with and without this feature.

5 Evaluation

The objective of this experiment was to analyse the performance of two movement response models by using additional virtual information in the planning and monitoring process. In order to test the advantages of human supervisory control, direct control was used as a performance comparison with the best human supervisory control.

Participants were asked to test the program and evaluate its performance. Result of our previous research in utilising mixed reality for a telerobotics interface [5] was applied to this interface. We continue to investigate telerobotics system control in terms of objective and subjective measures for both human supervisory and direct control.

5.1 Experimental Setup

In this experiment, the telerobotics interface and the supervisory functions were built into a gaming engine. A gaming engine offers a sophisticated environment, which enables us to create the replica models of a remote machine, including the kinematics; to have integrated input devices and sensors (e.g. joystick, keyboard + mouse, haptics); to provide an immersive environment for the operators; and to allow client server communication. Therefore, this experiment setting was divided into two areas, the user interface at a client site and remote manipulator at a server site.

In the client site, a 32” monitor was used as the main screen with a resolution of 2560 x 1600 pixels, which showed the telerobotics mixed reality interface (including the 3D model and live video) from the remote location to the participants. A standard keyboard and mouse was used as the input devices to deliver commands from the human operator to the interface (client machine). A computer server was located at the remote location to communicate with the user interface, and a robot arm used as a manipulator was connected to the server. An IP camera was also attached at the remote location to capture video information and provide it for the interface. Besides providing video streaming information, this camera was also connected to the server to work as a tracking system to provide updates on the position of the target objects through image analysis.

5.2 Participants

The experiment was conducted with a total of 24 participants. They were selected by using participants driven sampling with a snow-ball sampling method. The participants consist of 79% male and 21% female with ages ranging from 16 – 37 years old (mean = 22.75, SD = 5.75 years old). All the participants have a background in university education. Most of them were computer users (13% used a computer less than 7 hours per week, 26% between 7 to 21 hours per week, and 61% used computers for more than 21 hours per week) and played computer games (50% played computer games for less than 7 hours per week, 25% between 7 to 21 hours per week, and the remaining 25% played for more than 21 hours per week). None of them had any background knowledge on telerobotics and were new to this prototype interface/system design.

5.3 Experimental Design and Procedure

The main task in this experiment was choosing a block and pushing it into a hole by following a generated path arrow. The initial robot and blocks positions were the same for each participant. All participants were required at the start to select one block by clicking its model. They were allowed to change their block by clicking on another block model which would automatically assign the remaining blocks as obstacles.

Based on the response movement models and visual planning information described, we grouped the experiment into four different models. They are the (1) Adaptation model with planning information; (2) Adaptation model without planning information; (3) Queue model with planning information; and (4) Queue model without planning information. The participants were randomly assigned to model-test sequences. Prior to the experiment, the participants received an explanation (10-15 minutes) regarding the aims of the experiment, the differences between the models and the task scenario. Participants did not practice prior to the experiment. A maximum of 180 seconds was allocated to perform the task for each model. During the experiment, a successful result was counted when the participants followed the path assigned and sunk a block into the hole during the time allocated. Completion times were also recorded when the participant sank the block in the hole. These variables were noted as objective measurements in analysing the performance of each model. Either prior or subsequent to the requested task with the supervisory control model, the participants were also asked to perform the same task using the manual/direct control model to be later compared with the best supervisory control model. A questionnaire using a 7 point *Likert* scale and open-ended questions were used as subjective measurements.

6 Results

6.1 Objective Measurement

Completion time was the first objective meassurement recorded in the experiment. The average completion time for successful result in four models tested was 77.35 seconds (SD = 38.41 seconds) with detail for each model shown in table 1.

Table 1. Completion time for successful result using each model tested

Model Tested	Mean	SD	Min	Max
Adaptation with Info	91.49 s	39.61 s	32.6 s	150.7 s
Adaptation non Info	73.75 s	36.58 s	30.2 s	163.0 s
Queue with Info	75.15 s	37.66 s	19.4 s	165.1 s
Queue non Info	71.41 s	27.55 s	27.8 s	125.4 s

This experiment showed that there was a relation between the probability of success and the completion time with the correlation coefficient of -0.62. To further study this relationship, we grouped the completion time into 3 groups, 0-60 seconds, >60-120 seconds, and >120-180 seconds. As shown in table 2, there was a significant relationship (p=0.000) between completion time and result of the experiment (success or failure).

Table 2. The distribution proportion of result experiment by group of time

Completion Time (seconds)	Result of experiment		p	χ^2
	Failure N(%)	Success N(%)		
0 – 60	2 (5.88)	32 (94.12)	0.000	35.29
>60 – 120	0 (0.00)	34 (100.00)		
>120 – 180	15 (53.57)	13 (46.43)		

Logistic regression was performed to analyse this relationship more deeply, and the results showed that the participants who took longer than 120 seconds to complete the task have a much lower probability of success compared to those groups who completed the task more quickly (OR=0.05, p=0.000). Detailed logistic regressions for each model are shown in Fig.6.

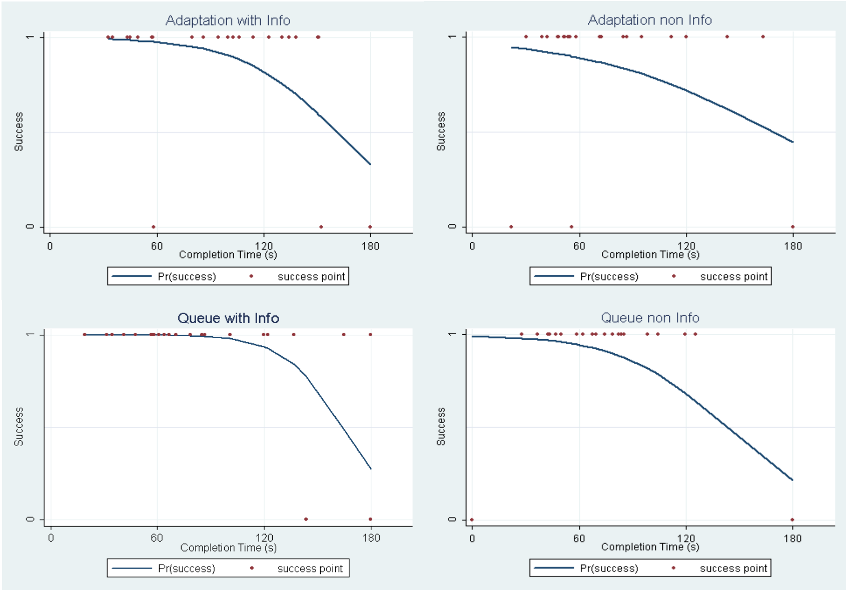

Fig. 6. Logistic regression showing the relationship between the probability of success and completion time

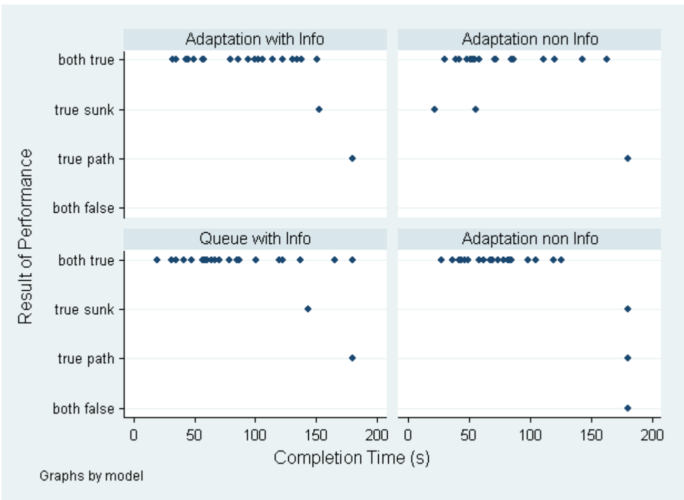

Fig. 7. Scatter plot – result of performance and completion time for four supervisory model tested

In this experiment, we recorded two variables, path and sunk, as indicators of the result of the experiment.

Based on Rijsbergen's equation [12], we used the F1-score to test the harmonic mean between precision and recall variable, in order to measure the performance from each model tested. The F1-score can be interpreted as a weight average of these two variables, with the best value at 1 and worst score at 0.

For classification task results, we categorise the correct path and the successfully sunk rocks as a correct result (True positive), the incorrect path with a sunk rock as an unexpected result (False positive), only the path is correct as a missing result (True negative) and the last category, neither path and sunk was correct as an absence of result (False negative). Then, by using these variables we calculated the value of precision and recall for each model and measured the F1-score (See Table 3 below).

Table 3. F1-score for each model tested

Model Tested	N	True positive	False positive	True negative	False negative	Precision (p)	Recall (r)	F1 Score
Adaptation with Info	24	20	1	3	0	0.95	0.87	0.91
Adaptation non Info	24	19	2	3	0	0.90	0.86	0.88
Queue with Info	**24**	**21**	**1**	**2**	**0**	**0.95**	**0.91**	**0.93**
Queue non Info	24	19	1	3	1	0.95	0.86	0.90

In this experiment, 83% of the participants used the stop function in at least one of the models tested, and these who used the stop functions in the adaptation model, were 8.4 times more likely to succeed compared with those who did not used these functions (p=0.05). On the contrary, there is no significant relationship between the utilization of stop function and result of experiments (success or failure) in the queue model (OR=0.66, p=0.6).

In comparison to the best supervisory control model tested, all twenty four participants performed an additional sub experiment to test the manual/direct control model using the same design task and experiment. As the result, we measure the precision value for this model as 0.70 where the recall value is 0.94. Further the F1-score for manual control is 0.80 which means the F1-score performance for the direct model is smaller than the best supervisory control model tested (Queue with Information), and also smaller than all supervisory models tested.

6.2 Questionnaire

Based on our participants' opinion, most of them agreed that all the supervisory models tested were user friendly (modus score for the four models were ranging from 5 to 7) and had good performance (modus score for the four models were ranging from 4 to 6). The Queue with extra information model was the most preferred out of the four supervisory control models tested (mean score = 4.67, modus ranging from 5 to 7). In addition, participants also agreed that the extra information in the model interface helped them in performing the task.

7 Discussion

The result showed that the Queue model perform slightly better than the Adaptation model (higher F1 score). In the Queue model, it seems that the participants had more control in their movement's planning. Even though in some situations they intervened by changing the path plan, it can easily be done with the available stop functions. Compared with the queue model, the stop functions were more helpful in the adaptation model since each time this model defined a new target position, the robot directly moved to the new target. In this scenario, the stop functions were useful to provide a condition for checking or cancelling the planning process. We also found that in performing either with the Adaptation or Queue model, most participants can successfully finish the task (by following the correct arrow and sink the block) less than 120 seconds, with the highest success under the Queue model with visual planning information.

The experimental results also showed that the models tested with visual planning information performed better than those without. The planning information, which was not sourced from the remote location, is useful in helping the participant to perform the scenario task, especially for the Queue model.

Comparing the performance between the best supervisory model (Queue with info model) and Manual/Direct control, participant using the supervisory model did better in following the path and sinking the block than participants using the manual/direct model. The movement planning function appeared to be an important feature which needed to be provided for telerobotics especially for the supervisory control model.

In addition to the objective measurement, we also asked our participants several open-ended questions about the interface performance. Participants were asked which features they were most attracted to and their suggestions for improving the interface performance. Based on the collected data, some of our participants said that the interface was enjoyable and fun. We thus argue that the gaming environment has played a significant role in creating an immersive atmosphere contributing to the participants' satisfaction. When asked about the features of the interface, most mentioned that they liked the functionality of the interface in providing information. As mentioned by one of our participants, "The mixture of 3D and video interface was useful for me because I can cross-check between each interface." This showed that the combination of 3D virtual and video view had assisted them in performing the task.

Moreover, three participants mentioned that they liked all features of our interface. Based on comments that we received from other participants, the viewpoint control, the graphic display and the additional information provided (e.g. green circle and lines) made our interface likeable. Furthermore, 17.6% of our participants emphasized that the most interesting feature for them was being able to use or control the interface easily, as expressed by the following response, "….. The use of the gaming key helped me to better control the robot arm and manage the 3D interface …. ".

8 Conclusion

The four supervisory models tested in this experiment showed better performance than direct/manual control. The queue response movement with visual planning information performed best. The visual planning information provided improved task performance. However, visual planning information did not have a large impact on performance in the Adaptable model probably because the participants do not plan very far ahead.

Even though the models tested showed good performance and received positive response from our participants, a number of suggestions for improvements in several aspects of the interface were provided. Most of the participants focused their comments on the 3D virtual views' performance. When they tried to operate the interface, they found several weaknesses in our 3D views, such as the precision, time delay and the stability of the 3D graphic. Due to these problems, our participants had a tendency to rely more on the video camera than they otherwise would have: "…. There were circumstances when we could see the robot arm touching the object on the video … but this could not be seen in the 3D model". This emphasises the need for mixed reality in interfaces to provide a mechanism that allows human interpretation to be applied where inaccurate sensing has introduced model errors. In practical telerobotics applications, incomplete models are common as a process that can be accurately modelled is probably amenable to fully automated control.

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