The influence of visualization on control performance in a flight simulator

Menja Scheer[1], Frank M. Nieuwenhuizen[1], Heinrich H. Bülthoff[1 2] and Lewis L. Chuang[1 ⋆]

[1] Department of Perception, Cognition and Action,
Max Planck Institute for Biological Cybernetics, Tübingen
[2] Department of Cognitive and Brain Engineering, Korea University
menja.scheer@tuebingen.mpg.de
frank.nieuwenhuizen@tuebingen.mpg.de
heinrich.buelthoff@tuebingen.mpg.de
lewis.chuang@tuebingen.mpg.de

Abstract. Flight simulators are often assessed in terms of how well they imitate the physical reality that they endeavor to recreate. Given that vehicle simulators are primarily used for training purposes, it is equally important to consider the implications of visualization in terms of its influence on the user's control performance. In this paper, we report that a complex and realistic visual world environment can result in larger performance errors compared to a simplified, yet equivalent, visualization of the same control task. This is accompanied by an increase in subjective workload. A detailed analysis of control performance indicates that this is because the error perception is more variable in a real world environment.

1 Introduction

We rely on visual feedback to ensure stable motion and collision avoidance during self-motion. Visual feedback informs the human operator of the immediate difference between his desired goal and the consequences of his action. Thus, subsequent actions can be planned to minimize this difference. For that reason, it is important to ask how error feedback should be visualized to support good control performance in the human operator.

The real world is a rich source of visual information for supporting the control of self-motion. For example, the rate and the focus of expansion in retinal image changes (i.e., optic flow) can respectively help us discern our velocity and heading direction [1, 2]. Given this, it is not surprising that virtual environments often strive to achieve high visual realism. This is especially true for flight simulators that are designed to train control performance, the success of which is subsequently vital for safety in a real vehicle. Several studies support this ambition. It has been shown in a flight simulator study that increasing the

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realism of ground terrain results in more accurate judgments in altitude as well as improved aiming [3]. Similarly, the altitude perception in pilots improved with higher object density in the visual environment [4].

Nonetheless, this strive towards high visual fidelity may not always be necessary nor helpful. For example, it has been shown in a disturbance tracking task that a simple instrument can better support the control performance of human operator than optic flow alone [5]. Similarly, a driving simulator study demonstrated that control performance is independent of whether a realistic view of the road or just the lane itself is presented [6]. Given these findings, it stands to reason that if all information necessary to complete a task could be condensed in a simple instrument, it might be possible to achieve similar performance as in a real-world environment. In fact, one might even expect better performance from a simple visualization that exclusively presents only the information that is necessary for performing a given task. This relieves the operator from parsing the environment for task relevant information.

To investigate whether or not control performance is dependent on the realism of the visualization, the present study evaluated human participants on a closed-loop control task in a high-fidelity, fixed-base flight simulator. The structure of the task is depicted in Figure 1. The reference signal $f_t(t)$ represents the target to be followed. This reference signal was an unpredictable change in the roll angle of the simulated vehicle. This was not directly shown to the *Human Operator*. Instead, only the difference $e(t)$ between the desired roll angle $f_t(t)$ and the output of the system $\varphi(t)$ was displayed. In performing this task, the *Human Operator* has to continuously perceive his deviation from the target and to manually operate a control device to minimize this perceived error.

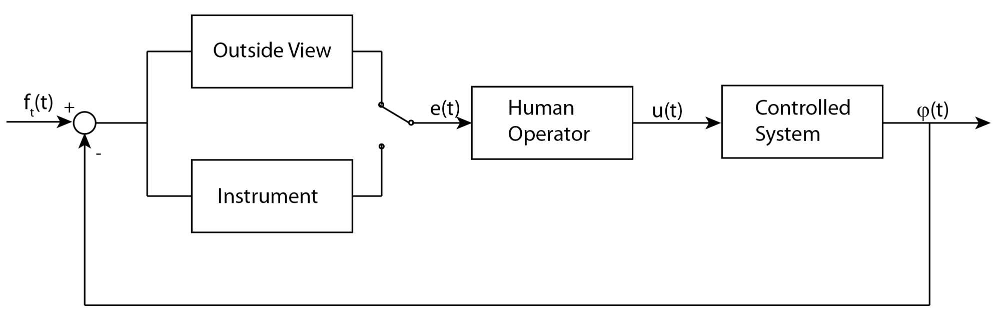

Figure 1. Closed-loop control task of the presented study. The difference $e(t)$ between the output of the system $\varphi(t)$ and the unpredictable reference input $f_t(t)$ was presented in two different ways. Either using a simplified instrumental view (*Instrument*) or a complex visualization showing the outside view of an helicopter (*Outside View*). The human operators' task was to compensate for the disturbance introduced through the reference signal.

In our implementation of this control scheme, the *Human Operator* moved a control stick to continuously compensate for the displayed error. Moving the stick to the left or right resulted in stick deflections that were proportional to the roll rate $\dot{\varphi}(t)$ of the simulated aircraft. Thus, stick manipulations served as a direct input $u(t)$ to a *Controlled System* with single-integrator dynamics. The output of the system was fed back and subtracted from the reference signal $f_t(t)$, resulting in the error $e(t)$ that was shown to the *Human Operator*.

As mentioned, there were the two possible visualizations for presenting this error feedback $e(t)$ to the *Human Operator*. This allowed us to investigate the influence of visualization complexity and was the only experimental manipulation in the current study. It is worth mentioning again that the reference signal $f_t(t)$ was the same regardless of the visualization. In other words, the task difficulty was the same regardless of the visualization shown. The *Instrument* visualization was comparable to an attitude indicator (commonly referred to as an artificial horizon), which is an aviation instrument that displays the aircraft's angular position with respect to the horizon (Figure 2). For the *Outside View* visualization, participants were presented with a view of a simulated real-world environment from an aircraft cockpit (Figure 3).

In the current study, we were interested in how the visualization of error feedback affected control performance. In addition, we were also motivated to know whether this influence of visualization would be accompanied by changes in subjective workload. To measure control performance, the output of the joystick $u(t)$ as well as the error $e(t)$ were recorded. $e(t)$ was the amount of error that remained in the system after the *Human Operator* resolved the continuous disturbance $f_t(t)$ to the system. Therefore, this value served as a basis for evaluating control performance. $u(t)$ was the amount of control input that the *Human Operator* submitted to the *Controlled System*. This was treated as a measure for control effort. To assess subjective workload, we requested participants to complete a computerized version of the NASA Task Load Index (NASA-TLX) questionnaire [7] after each given visualization.

2 Methods

2.1 Participants

Twelve participants (eight male), were recruited from the participant database of the Max-Planck Institute. They were aged between 21–37 years (mean: 29.1 years) and had normal or corrected-to-normal vision. All were right handed. They gave their written consent before the experiment and were paid 12 Euros per hour.

2.2 Apparatus and Flight Model

The current study was conducted in a fixed-based flight simulator that consisted of a main PC and display cluster. The main PC controlled the experiment and data collection with a customized software based on Matlab Simulink (Mathworks). This PC was connected to a cluster of nine independent visualization PCs, via a local area network and commanded the timing and presentation of the visualization using UDP triggers.

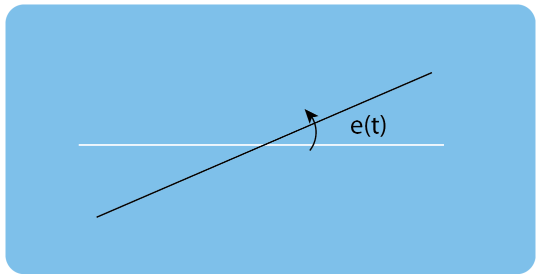

Figure 2. *Instrument* condition, showing an artificial horizon. The error $e(t)$ is calculated from the reference signal $f_t(t)$ and the roll angle $\varphi(t)$.

The visualization PCs were connected to a large display that consisted of nine panels (total field-of-view: 105° x 100°). In the *Instrument* condition, two lines were rendered on a blue background with Matlab Psychtoolbox, a black line that represented $e(t)$ and a white horizontal line that represented zero error [8, 9] (Figure2). The *Outside View* condition used flight simulation software (i.e., FlightGear; [10]) to present a cockpit view of a straight-ahead flight path, through the hinterlands of San Francisco, wherein $e(t)$ resulted in rotations of the cockpit's view frustum and, hence, the entire scene (see Figure 3).

Inputs to the *Controlled System* were submitted via a joystick (Extreme 3D Pro, Logitech) that sampled at 256Hz. This only affected the roll angle of the visualization. The other degrees of freedom of the *Controlled System* were fixed.

A computerized NASA-TLX questionnaire was presented to the participants for the self-reporting of subjective workload via a laptop computer. This rating scale consists of six sub-scales (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, Frustration) [7].

2.3 Compensatory Tracking Task

In a compensatory tracking task, the participants needs to minimize the error between a target signal and the output of the system. In the current study, a disturbance $f_t(t)$ is continuously introduced into the system, which exclusively perturbs the roll angle of the *Controlled System*. Here, $f_t(t)$ was designed as quasi-random reference signal that consisted of a sum of 10 sine waves. These comprising sine waves were non-harmonically related. The disturbance function had a variance of 1.7 deg^2. More specifically we used the following function [11]:

Figure 3. Fixed-base flight simulator, consisting of nine panels and a field-of-view of 105° x 100°. Here the *Outside View* is shown. During the experiment, visual disturbances were experienced in the roll-axis around the horizon, that our participants were instructed to compensate for with the provided joystick

$$f_t(t) = \sum_{j=1}^{N} A(j) sin(\omega(j) \cdot t + \phi(j)) \tag{1}$$

The amplitude, frequency and phase of the sinusoids are given in Table 1.

j	A_j in deg	ω_j in rad/s	ϕ_j in rad
1	1.351	0.377	0.145
2	1.007	0.859	0.902
3	0.509	1.759	4.306
4	0.260	2.827	6.127
5	0.157	3.917	5.339
6	0.095	5.466	6.155
7	0.060	7.749	1.503
8	0.043	10.514	1.506
9	0.036	13.132	2.368
10	0.030	17.363	2.086

Table 1. Values of the ten non-harmonically related sine waves of the target signal $f_t(t)$. With number of the sine wave j, the amplitude of the j_{th} sine wave equals A_j, the frequency is ω_j and the phase is ϕ_j

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2.4 Procedure

Two sessions comprised the full experiment and were conducted on separate days. Two blocks were performed in each session and each block presented one of the two possible visualizations (*Instrument*, *Outside View*). Three 5 mins trials were presented per block, with 5 mins breaks between them. The order of the blocks was counter-balanced for the visualization condition across sessions and participants.

Each session began with the participant reading and signing a consent form that provided experimental instructions. The computerized NASA-TLX questionnaire was administered after the completion of each block of trials for the given visualization condition. Altogether, the experiment took 3.5 hours for every participant over the two sessions.

2.5 Data collection and analysis

To evaluate the performance, the normalized root mean squared value of the error signal $e(t)$ (nRMSerror) was calculated, as well as the root mean squared value of the control input $u(t)$ (RMSinput). The nRMSerror was normalized with the disturbance that was experimentally introduced to the system. Thus, a nRMSerror that is smaller than a value of 1 would indicate that our participants reduced the disturbance in the system, while a value that was larger than 1 would indicate that the participant introduced additional disturbances to the system. The nRMSerror can be further divided into the mean and variable error as follows:

$$nRMSerror = \sqrt{MeanError^2 + VariableError^2} \tag{2}$$

whereby $MeanError$ is simply defined over all measured time points i as,

$$MeanError = \frac{\sum_{i=1}^{N} e_i}{N} \tag{3}$$

and $VariableError$ as,

$$VariableError = \sqrt{\frac{\sum_{i=1}^{N} (MeanError - e_i)^2}{N}} \tag{4}$$

The mean error represents the distance of the mean of the error distribution from zero (i.e. the target) and the variable error represents the spread of the error distribution [12].

The RMSinput represents the control effort of the participants. A higher RMSinput indicates that the participants submitted more joystick input into the *Controlled System*.

These measures for control performance, control effort and subjective workload were submitted to a paired-sample t-test to test for statistical differences. An alpha-level of 0.05 was adopted as the criterion for significance.

3 Results and Discussion

Figure 4A shows that the *Outside View* visualization resulted in a larger nRMSerror than the *Instrument* visualization (t(11)=-6.54, $p < 0.05$). In fact, all of our participants had nRMSerror values that were larger than 1 when the *Outside View* visualization was presented. This means that their efforts to minimize error actually led to additional disturbances in the control system. It is necessary to point out that this was not due to the difficulty of the compensatory control task per se. When presented with the *Instrument* visualization, all participants were able to achieve nRMSerror values that were lower than 1. This result highlights the critical influence of visualization on control performance.

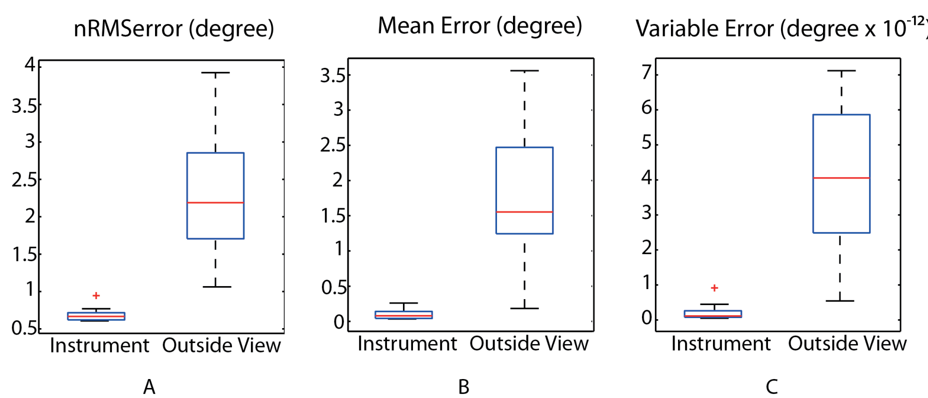

Figure 4. Box-plots for the measures of nRMSerror (A), mean error (B) and variable error (C) across the condition of Visualization. Each box-plot shows the median, the interquartile range and data range. Outliers are represented as red crosses.

There are several explanations for this large difference in nRMSerror. First, our participants have failed to accurately estimate the desired goal from the *Outside View* visualization. Namely, the ideal attitude. If so, we would expect our participants' error distribution to be shifted away from the zero value, resulting in a bigger bias (e.g. mean error). Next, our participants could have been unable to accurately estimate the error from the *Outside View* visualization. If this was true, we would expect a high variable error. Figures 4B and 4C show that the mean error and the variable error were both larger for the *Outside View* compared to the *Instrument* condition (Mean Error: t(11)=-5.77, $p < 0.05$; Variable Error: t(11)=-6.02, $p < 0.05$). Therefore, our participants were less certain about the ideal state and were less precise in their control when they were presented with an *Outside View* visualization.

A time trace of the control error for both conditions (Figure 5) shows these two differences between the conditions. In the simple *Instrument* condition (light gray), the control error varied around the target with smaller mean and variable error. In the *Outside View* condition (black) the mean error is shifted over time with larger fluctuations around it.

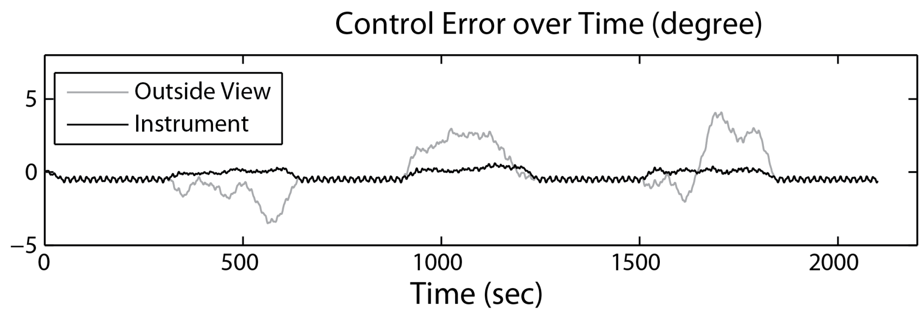

Figure 5. Control error over time for the *Outside View* (light gray) and *Instrument* (black) condition. The data was filtered using a moving average filter with a window size of 40 seconds. In the *Instrument* condition the error varied around the target while in the *Outside View* condition, the mean of the error distribution is shifted over time.

In addition, the *Instrument* condition resulted in more input activity than the *Outside View* condition (t(11)=5.59, $p < 0.05$; see Figure 6). This indicates that the *Instrument* visualization induced our participants to invest more control effort into the task than for the *Outside View* visualization. This could be because error was better perceived from the *Instrument* visualization, resulting in more and better targeted control input. Conversely, participants could have submitted less control input in the *Outside View* visualization because they did not perceive the need for it.

Subjective workload, as measured by the NASA-TLX scores, did not differ across the visualization condition (t(11)=2.07, $p = 0.07$). This supports our earlier conclusion. Although the participants did not perceive a difference in the difficulty of the same task across the different visualizations, the difference in their ability to accurately perceive their error resulted in very different control performance. The NASA-TLX scores indicate that mental demand (23%), performance (29%) and effort (23%) comprised more than 70% of the perceived workload in our task.

These findings show that control performance is better supported by a visualization that explicitly present the information that is required for the control task. In the current experiment, an explicit representation of the error supported the *Human Operator* in submitted the appropriate control inputs, without increasing his perceived workload. Unfortunately, competence in a complex control task such as piloting an aircraft with many degrees of freedom for a large repertoire of possible maneuvers often depend on multiple sources of information. It may not be feasible to create dedicated instruments for every relevant information channel. In this regard, the outside world might represent a more general

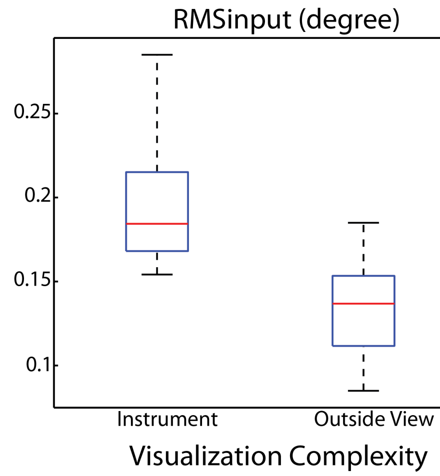

Figure 6. Box-plots for RMSinput across the condition of Visualization. Each box-plot shows the median, the interquartile range and data range.

and effective source of information than spreading one's visual attention across multiple instruments. This warrants further investigation.

In conclusion, the visualization of the error feedback can result in different levels of performance for two experimental conditions that are equivalent in terms of their difficulty and perceived workload. A simple visualization might lack the qualities of physical realism, but explicitly represents the primary property that is of interest to the human operator. This has the advantage of preventing the occurrence of unintended biases in error perception.

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