Understanding Cognitive Behavior in Collaborative Control Rooms through Eye Tracking

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Abstract

In the digital era, industrial control rooms have transformed into collaborative workstations. This shift, while technologically advanced, introduces challenges to operators, such as information overload, testing the limits of human cognitive processing. Consequently, understanding operators' cognitive behavior in these collaborative environments has become essential to enhance operational efficiency and safety. Studies have shown that eye tracking is a valuable tool for understanding operator behavior. However, its application faces limitations in collaborative control room settings due to the presence of multiple and overview displays at varying heights. This work addresses this gap by introducing a novel methodology that integrates eye-tracking data with a three-dimensional (3D) model of a control room, enabling a comprehensive visualization of operator gaze patterns and cognitive behavior. The accuracy and precision of the recorded gaze were tested by studies involving human subjects. Additionally, we conducted a case study using a simulated control room environment, demonstrating the practical applicability of our methodology. This case study provided valuable insights into how operators interact with and respond to different elements in a collaborative control room, underscoring the potential of our method in capturing and analyzing cognitive behavior in real-world scenarios.

**Keywords**: Cognitive behavior, Collaborative control rooms, Eye-tracking, Operator performance, Safety.

* 1. Introduction

Control rooms are evolving into collaborative spaces in today's digitized process industries. Examples such as ABB's Extended Operation Workstations and BAW Architecture's Integrated Operation Center highlight this trend toward centralizing operations in a unified space (Borås & Sverige, 2021; BAW Architecture, 2018). These advanced environments combine individual operator panels with overview displays, essential for team-based access and decision-making. However, with the influx of data facilitated by automation and AI, operators face the challenge of information overload. This can impair judgment and decision-making, increasing cognitive workload and the likelihood of errors. Understanding operator behavior, especially under high cognitive demands, is crucial. Operators need to effectively switch focus between individual and overview displays, requiring a mix of individual task comprehension and efficient teamwork.

Recently, eye tracking has been used to understand human cognitive behavior in various safety-critical domains. For instance, an eye-tracking study reported that novices frequently shifted their gaze across multiple information sources, indicating a potential unfamiliarity with the ongoing abnormality of the process (Wu et al., 2020). Our findings from previous work revealed that operators well-versed in process dynamics predominantly focused on key process variables related to the situation at hand (Bhavsar et al., 2017). We have also developed a mathematical framework to decode operators' mental representations of process dynamics (Shahab et al., 2022).

The above studies are limited to cognitive behavior studies within conventional control room settings like single-screen setups. This narrow focus has restricted our understanding of operator behavior in the collaborative environment of modern control rooms, which often feature an array of multiple and overview displays. Such multi-screen settings introduce unique challenges, particularly when operators collaboratively navigate and respond to abnormal scenarios. More recently, we have shown the application of eye-tracking to encompass multi-screen, multi-user control room environments, revealing considerable variations in attention and gaze patterns among operators (Shajahan et al., 2023). Building on this foundation, our current work extends the scope even further. We aim to provide a more comprehensive understanding of operator cognitive behavior, considering the additional complexity introduced by the overview display. This approach not only enriches our understanding of the operator’s cognitive behavior and decision-making strategies but also paves the way for more effective training and operational strategies tailored to the realities of modern control rooms.

* 1. Proposed Methodology

We propose a methodology to analyze operators' cognitive behavior in collaborative control rooms by visualizing their gaze patterns and obtaining eye-tracking metrics. Traditional eye trackers can capture gaze data on calibrated displays within a predefined range. However, they fall short in capturing gaze data on large overview displays, primarily due to their substantial size, and relying solely on a single-eye tracking system is insufficient. In our approach, the key to extending gaze tracking to overview displays lies in using gaze vector data, a fundamental output of standard eye-tracking systems. The gaze vector represents the direction in which the user is looking. In our methodology, we repurpose this gaze vector, applying it to visualize eye movements on the overview display found in collaborative control rooms. We utilize this data without physically altering the eye-tracking apparatus or its orientation. Instead, we project the gaze vector onto the overview displays. This is technically achieved by integrating the gaze vector with a 3D model of the control room.

The 3D model is constructed using photogrammetry, a technique that employs multiple photographs taken from various angles. Once we have the 3D model, we employ ray casting. This technique, common in computer graphics, involves projecting rays from a point—in our case, from the origin of the gaze vector—into the 3D space and determining where these rays intersect with the 3D model. We used PyVista visualization toolkit available in the Python programming language. Subsequently, the intersection of the gaze vector with the 3D environment is visualized by representing them as small spheres within the 3D model. This allows us to accurately trace the paths of the operators’ gaze as it moves across different control room displays, including the overview displays.

The methodology was validated in an experimental setup emulating a collaborative control room with multi-screen displays. This setup included three 22-inch monitors in a triple-monitor setup (which are calibrated to the eye tracker) and a 170-cm (67-inch) projector screen as the overview display (uncalibrated) placed at a 52 cm distance from the center display (fig. 1). an eye tracker with three infrared cameras was used to track the eye movement in this setup. Human-subject studies were conducted to validate the proposed methodology's accuracy and precision and show its potential application in a collaborative control room. Next, we discuss the protocol of the human subject studies.

*2.1. Human Subject Studies*

Our first series of experiments aimed to assess the accuracy and precision of our methodology by employing a technique similar to that used for traditional eye-tracking studies (Tobii, 2020; Feit et al., 2017). Accuracy, the average angular offset between the target and recorded gaze vectors, and precision, the gaze data's standard deviation from its mean value, are crucial metrics for evaluating the reliability of our method, especially given the challenges of adapting eye tracking to large, uncalibrated displays. We conducted controlled experiments in the previously discussed setup with participants focusing on nine calibration points. These points were strategically placed at 7, 21, and 31 degrees of angular height, spanning the entire size of the overview display.

Figure 1: 3D model of the collaborative control room, with small spheres are gaze fixation points for a specific task performed by a participant, and the 3D line (gaze direction vector) connecting eye to the fixation point.

Beyond technical validation, our methodology underwent real-world testing in a study involving four postgraduate students from IIT Madras who played the roles of control room operators. They were instructed through video and PDF handouts to understand chemical processes and utilize valves to rectify abnormalities and restore normal operation. They interacted with a four-screen chemical process simulator in a typical collaborative control room setup, as discussed previously (Fig. 1). This setup included various displays: a central screen showing the plant's schematic interface, a screen for process trend analysis, a screen for alarm summaries, and an overview display for monitoring key process variables trends of the chemical plant. Time-based information such as trends aids operators in understanding the past and present states of the process, thereby boosting their capabilities to make a prognosis (Bennett et al., 2005).

* 1. Results

This section presents the results of our experiments, focusing on the accuracy and precision of our methodology. Using a case study, we also demonstrate the potential of the proposed methodology for understanding the operator’s cognitive behavior in a collaborative control room setting.

*3.1. Accuracy and precision*

Table 1 presents the average accuracy and precision obtained from ten participants, giving a detailed view of the performance at different viewing heights on the overview display.

For the overview display, central to our study and not typically covered by standard calibration, we observed an average accuracy of 2.4 degrees and a precision of 5.8 cm(horizontal) and 2.8 cm(vertical) across all heights. We further analyzed the accuracy and precision at individual angular heights relative to the user’s horizontal visual lines on the overview display. Table 1 shows that at the height of 7 degrees, the average accuracy was recorded as 2.5 degrees with a precision of 3.9 cm (horizontal) and 3.1 cm (vertical). At greater angular heights of 21 and 31 degrees, we found similar levels of accuracy (2.7 and 2.2 degrees). However, the precision in the horizontal plane decreases as the angular height increases, indicating degradation in eye gaze data quality.

Table 1: Accuracy and precision of the methodology at three angular heights of the overview display.

|  |  |  |  |
| --- | --- | --- | --- |
| Angular height  (degrees) | Accuracy  (degrees) | Precision (centimeter) | |
| **Horizontal** | **Vertical** |
| 7 | 2.5 | 3.9 | 3.1 |
| 21 | 2.7 | 6.0 | 2.0 |
| 31 | 2.2 | 7.6 | 3.3 |

Despite challenges of large size and beyond the range of calibrated displays, the overview display maintains good precision and accuracy. The results are comparable to those of accuracy and precision in a controlled environment (Feit et al., 2017). Notably, the overview display in collaborative control rooms typically features less dense information with larger areas of interest. Our results indicate that the eye gaze on the overview display can provide valuable insights into operators' attention patterns.

Next, we will demonstrate the effectiveness of the proposed methodology in capturing cognitive behavior in a collaborative control room setting.

*3.2. Case study*

The case study involves a simulated chemical process simulator, as discussed previously. Participants played the role of operators. They were asked to monitor and intervene during abnormalities. During the task, participants encountered a disturbance in the reflux ratio of the distillation column, which triggered alarms at tray temperatures. This required them to adjust the reflux valve to bring the process to the operating limit. Therefore, the tray temperatures and the reflux valve are the relevant sources of information for this task, and all other variables are irrelevant.

Table 2 shows the percentage of time spent by the participants on the relevant and irrelevant information sources on each display, as captured by fixation duration. This was obtained by ray casting of the participant’s gaze on the 3D model of the experimental setup.

Table 2: Percentage of time the participants spent on various displays' information sources.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Participant | Overview display | | Schematic display | | Trend  panel | Alarm summary |
| Relevant | Irrelevant | Relevant | Irrelevant |
| 1 | 32.0 | 2.8 | 27.0 | 25.4 | 12.4 | 0.0 |
| 2 | 39.9 | 1.0 | 20.0 | 22.0 | 16.6 | 0.6 |
| 3 | 14.6 | 0.7 | 18.2 | 46.8 | 6.4 | 13.1 |
| 4 | 4.9 | 1.3 | 24.4 | 47.0 | 22.5 | 0.0 |

Consider participant 4, who spent 48.3% of the total time on irrelevant information sources, indicating a lack of awareness about the disturbance's root cause (Table 2). Additionally, they allocated 6.2% of their time to the overview display, suggesting a limited understanding of using time-based information to anticipate control action effects.

In addition, participants three and four devoted almost half of the time (47.5% and 48.3%, respectively) to irrelevant information sources, indicating a lack of understanding of the process dynamics. As a result, participants three and four took more time (127 s and 130 s) to complete the task. In contrast**,** participants one and two are more attentive to relevant information sources related to a disturbance in reflux ratio (71.4% and 77.1%, respectively). They dedicated nearly one-third of their time to the overview display, efficiently monitoring the impact of their actions on the process. The process trend indicates a proactive monitoring strategy of these participants, a characteristic of experts. The relatively lower attention of participants three and four indicates that they were unaware of the effect of their control action and adopted a reactive strategy (a characteristic of a novice) to deal with the abnormal situation. Thus, the proposed methodology effectively captures the participant’s understanding of the process dynamics in a collaborative control room setting. The results align with the previous studies in a controlled control room environment with participants interacting with the process via a screen display (Sharma et al., 2016).

Our proposed methodology effectively captured 254 fixations on the uncalibrated overview display, showcasing its excellence in capturing operator focus. In contrast, the traditional eye-tracking techniques failed to register any fixations on the uncalibrated overview despite having 254 fixations captured by our approach. Both methodologies adeptly capture attention on the three calibrated displays. This absence of fixation on overview display, evident in the traditional eye-tracking techniques, highlights the crucial role our proposed approach plays in revealing nuanced attention patterns that would otherwise go unnoticed.

* 1. Conclusions

In this paper, we proposed a methodology to understand the operator's cognitive behavior using eye tracking within modern collaborative control rooms. This is achieved by integrating eye gaze data with a 3D model of the control room, providing a detailed visualization of gaze patterns and eye-tracking metrics to understand the operators' cognitive behavior and attention dynamics. The technical validity of our methodology was demonstrated through conventional accuracy and precision metrics for eye gaze data validation. The potential of the proposed methodology in capturing the operator’s cognitive behavior is demonstrated using a case study on a chemical process simulator. The findings revealed that operators, when completing a disturbance rejection task efficiently, consistently focused on process trends displayed in the overview display. This nuanced observation underscores the significance of our methodology, as traditional eye-tracking methods might overlook operators' attention to the overview display, providing an incomplete depiction of cognitive behavior. The insights gained from this work could significantly improve human performance, particularly in understanding cognitive behavior in modern control rooms. Our future work will develop additional eye-tracking metrics tailored to comprehend individual and team cognitive behavior in collaborative control rooms.

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