Design of Gaze-Based Alarm Acknowledgement by Parameter Characteristics

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Abstract. Alarms in industrial control rooms are defined by their ability to alert an operator of abnormal events that require prompt response. However, when vigilant, operators may anticipate upcoming alarms, rendering those alarms less informative if not a nuisance. Three gaze-based alarm acknowledgement methods were designed by estimating operator awareness based on their eye fixations on the parameter/area of interest and parameter behavior shortly before the alarm. The three designs differed in acknowledging the types of parameter behaviors, which could be: a) near the alarm threshold, b) fluctuating drastically, or c) trending towards an alarm threshold. These three parameter behaviors correlate with increased visual sampling, which suggests higher operator awareness or expectation of alarms. In a simulator study comparing the three gaze-based acknowledgement methods against no gaze acknowledgement, 24 participants completed 24 trials of alarm monitoring task while maintaining a single parameter within a predefined range. Analysis of variance revealed that usability ratings were higher for conditions with than without gaze acknowledgements, demonstrating promise for this alarm management approach.

Keywords: Eye tracking · Alarm management · Gaze-based interaction · Process monitoring

1 Introduction

Industrial control room alarms alert operators to abnormal events for prompt response; however, alarm informativeness changes with respect to monitoring behavior, making expected alarms potentially nuisance [1–4]. Both focused and selective attention [5] of the operator for mitigating abnormal events may be compromised if alarms are uninformative, difficult to ignore, and onerous to manage [6]. To alleviate operators from attention and workload demand of managing alarms, we designed three gaze-based alarm acknowledgement methods that estimated operator anticipation of impending alarms and reduce the salience of alarm presentation to match the amount of redirection needed.

Inspiration for this interaction design came from previous work on Attentive User Interfaces (AUI) [8]. AUIs use gaze, scan paths, body orientation, and/or proximity to

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determine the location of the display/environment that a person is attending, and alter the interface based on the indirect estimation/computation of user attention [7]. AUI essentially uses the design metaphor of a dialogue that requires turn-taking and eye contact to determine whether interruption is timely and aligned with the user's priorities [8].

Like AUI, our design for gaze-based acknowledgement focuses on adapting the display and interaction based on the operator's attention estimated with eye tracking data. Utilizing eye-tracking enables unobtrusive estimation of the operator awareness of parameters and passive acknowledgement of alarms, alleviating operators from distraction and manual acknowledgment. This gaze interaction design is envisioned as additional support to manual acknowledgement in traditional alarm systems. A successfully implemented gaze interaction system that reduces anticipated alarms could improve the safety of industrial operations by increasing the speed at which those nuisance alarms are acknowledged, thereby reducing the distraction from less informative alarms.

The remainder of this paper is organized as follows: Sect. 2 describes the three gaze-based acknowledgement methods; Sect. 3 describes the human-participant study and reports the results of our analysis on usability; and finally, conclusions of our work are presented in Sect. 4.

2 Three Designs

The primary objective of gaze-based acknowledgement is to adjust the salience according to operator awareness. Flashing and loud auditory cues of an alarm force the operator to reorient their attention and are difficult to ignore any peripheral cue, regardless of its informative nature or validity [6].

For this reason, our gaze-based acknowledgement, when activated, reduces the alarm salience by eliminating audio alert and replacing the yellow highlight of the parameter with a yellow outline (Fig. 1). The gaze-based acknowledgement design deliberately maintains a visual marker to communicate that the alarm is unresolved while reducing salience on an alarm that operator likely has awareness of. For activating the gaze-based acknowledgement that reduces the alarm salience, three methods based on two conditions have been investigated: 1) the operator's fixations on the parameter/Area of Interest (AOI), and 2) parameter behavior associated with increased visual sampling.

The first condition is met (for all three methods) when there are at least two fixations on the parameter or AOI during a short 3-s window prior to the alarm (i.e., t-4 to t-1 until the alarm where t denotes time in Fig. 2). A minimum fixation threshold was set because of the association between the number of fixations and dwell duration on relevant AOI and operator manual performance [9]. Similarly, a fixation cluster that occurs before an event has been interpreted as anticipation [10]. For these gaze-based alarm acknowledgement methods, fixations were computed with the Velocity-Threshold Identification (I-VT) algorithm, which distinguishes fixations from saccades based on the difference in angular speed [11]. The 3-s time window was derived from intention-based research in the automotive industry which has shown that a three to five second window was the most accurate for predicting intention [12]. Our design disregarded fixations that occurred less than one second before the alarm occurs because the time

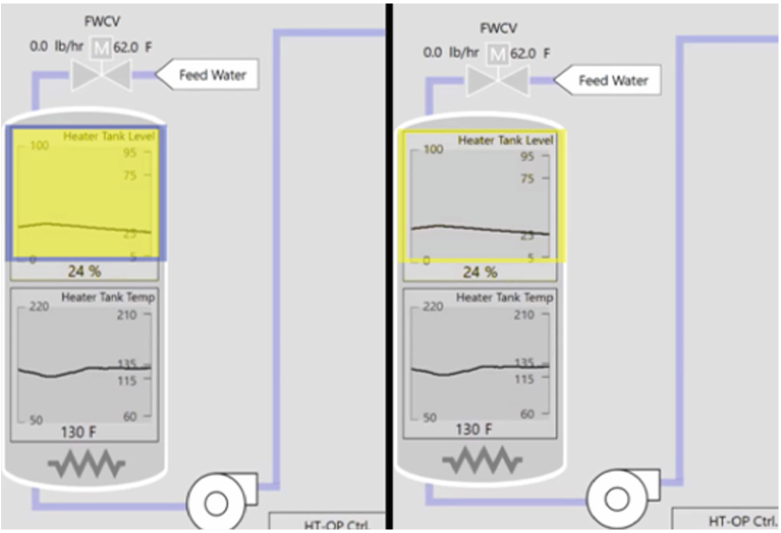

Fig. 1. Alarm without gaze-acknowledgement (left) versus alarm with gaze-based acknowledgement (right).

interval between the glance and alarm would likely be too short for a human to anticipate the alarm in an endogenous manner.

The second condition is based on the parameter behavior of the impending alarm shortly before occurrence. In other words, acknowledgement is driven by the characteristics of the parameter trendline. Research indicates that an operator's visual sampling changes with respect to parameter behaviors, thereby indicating increased attention and subsequent alarm anticipation. Our three designs vary based three types of parameter behavior that is: a) near the alarm threshold, b) fluctuating drastically, or c) trending towards an alarm threshold. Therefore, the three designs were named Proximity-based (Sect. 2.1), Entropy-based (Sect. 2.2), and Prediction-based (Sect. 2.3), respectively. Figure 2 illustrates how the gaze-based acknowledgement methods function by example.

2.1 Proximity-Based Acknowledgement Method

Operators increase their visual sampling rate on parameters near the control limit [13, 14]. In some cases, operators set mental targets for when they need to watch a parameter value more closely, which are more conservative than the original alarm settings [15, 16]. Similarly, [17] observed that operators tightened alarm limits, creating pre-alarms, if they suspected that parameters would drift. This implies that when a parameter is at risk of reaching abnormal values, operators would monitor the parameter more closely to make sure those parameters do not alarm. These findings suggest that frequent sampling of a parameter near its control limit is likely correlated with the expectation of an alarm.

Therefore, in addition to counting fixations, the proximity-based method would acknowledge an alarm only when the parameter value exceeded the acknowledgement thresholds from the past four seconds. The gaze acknowledgement thresholds were

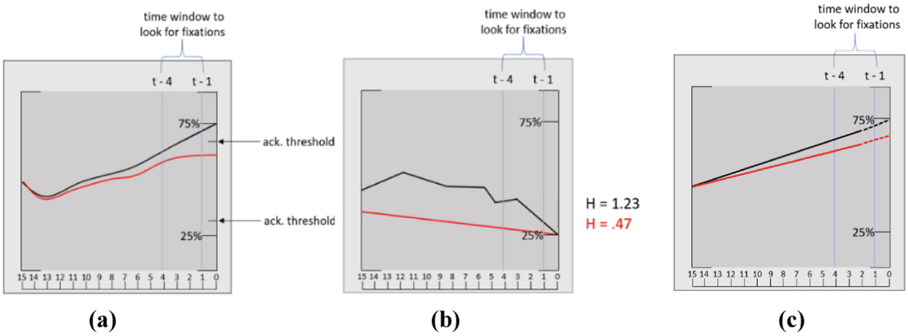

Fig. 2. Each graphic shows an instance where the gaze-based acknowledgement methods would activate (black trendline) and an instance where it would not (red trendline). X-axis represents time scale in seconds and y-axis represents parameter scale in percent across (a) to (c). (a) Proximity-based acknowledgment method, (b) Entropy-based acknowledgement method, and (c) Prediction-based acknowledgement method. (Color figure online)

another static threshold set at 10% and 90% of the operable range between the high and low alarms of the parameter (e.g., for a parameter with an operating range of 25 to 75% the acknowledgement thresholds would be at 30 and 70%). These acknowledgement thresholds were not displayed on the parameter but determined activation of the acknowledgement. Figure 2a depicts an instance of when acknowledgement would occur for this method (black line) and an instance where it would not (red line).

2.2 Entropy-Based Acknowledgement Method

Monitoring behavior is also influenced by the entropy or fluctuation level of the parameters. Fluctuating parameters are less predictable than stable ones and provide more information per visual sample. Models of monitoring behavior emphasize that operators tend to sample parameters to maximize their return value of information on each gaze [13, 18]. Operators often would not visually sample a parameter until their perceived entropy was sufficiently high [19]. Slope variability of a parameter hindered a person's ability to predict future values, and therefore induced higher visual sampling rates compared to parameters changing at constant rates [20]. These behaviors suggest that operators sample parameters with high entropy more often. A frequently monitored parameter due to the constant risk of an alarm would suggest a higher likelihood that the operator would know when an alarm would occur.

The entropy-based method acknowledges an alarm when the entropy of parameter over the past 15 s exceeded 1.2 and if two or more fixations occurred within the set time window of four seconds prior to the alarm. Entropy of the parameter was calculated using a histogram estimator of the parameter value frequencies during the past 15 s (i.e., the amount of time visible on the trendline) [21, 22]. The entropy threshold was determined by the simulator used for this study by calculating the average entropy of a parameter that would crest and drop at least three times in the last 15 s. Figure 2b depicts an instance of when acknowledgement would occur for this method (black line) and an instance where it would not (red line).

2.3 Prediction-Based Acknowledgement Method

Operators also rely on parameter trends to inform their expectancy of alarms. Trend graphs reveal patterns of past data, allowing operators to predict future behavior [23]. When watching random step changes of a dial, [24] observed that a person's estimation of the next value was the difference between their current observation and the average change of their earlier observations. This shows that people rely upon past visual sampling to systematically estimate the next value. Similarly, an operator's estimation of parameter values has been modelled as calculating the likelihood of a parameter reaching a self-set limit [15]. The more consistent the trendline has been, the smaller the range of the probability distribution curve. Empirical studies have shown that fixation frequency is positively correlated to parameter's rate of change [20, 25]. Together, these studies suggest that an operator has greater expectancy of an impending alarm when the parameter shows a steady slope.

The prediction-based method would acknowledge an alarm when the parameter value was predicted to exceed the alarm thresholds using an equation derived from past values to forecast the future trend of the parameter. To predict whether the parameter would exceed the alarm threshold in the next three seconds, a second-degree polynomial curve was fitted based on parameter's value over the past 15 s for predicting parameter values. Figure 2c depicts an instance of when acknowledgement would occur for this method (black line) and an instance where it would not (red line).

3 Preliminary Evaluation

A simulator study compared the three gaze-based acknowledgement methods against no gaze acknowledgement/control with 24 trials of a dual-task. Additional details of the human-participant study can be found at [26]. The 24 participants were Virginia Tech students (M = 14, F = 10, age 18–45). Participants were tasked with keeping a single parameter in range that would randomly drop in value. Simultaneously, participants monitored seven other parameters of a chemical plant simulator for alarms and marked their prediction of an alarm to occur with 4 s by clicking on the parameter. Participants received training and practice for both tasks. Participants completed four blocks of six trials followed by a three-item usability questionnaire. Presentation of acknowledgement methods was fully counterbalanced (i.e., $4! = 24$). Participants were given a 2-min break between each block and recalibration took place. After four blocks, participants were debriefed and compensated for their time.

The usability questionnaire was used to determine participants' perception of the usefulness of each acknowledgement method. A one-way Analysis of variance (ANOVA) with a fixed factor of alarm acknowledgement method and a random factor of participant was conducted. Usability ratings were averaged across the three items for every block of trials per participant. The usability scale showed a Cronbach's alpha ($\alpha = 0.829$), a sufficiently high internal consistency across the three items (i.e., $\alpha \geq 0.8$). Two participants were omitted based on questionnaire incompletion ($N = 22 \times 4$). The usability ratings were not normally distributed (Shapiro-Wilk test $W = .0167$, $p = 0.017$, $\kappa = -0.389$, $S_{kp} = -0.305$). However, the type I error rate for non-normal data for ANOVA should remain within the bounds of Bradley's criterion (i.e., .025 and .075) if κ or S_{kp} is between

−1 to 1 [27, 28]. The sphericity assumption was satisfied according to the Mauchly criterion ($X^2(3) = 3.836, p = 0.573$). The ANOVA revealed that subjective usability ratings were higher for conditions with than without gaze acknowledgements ($F(3,63) = 3.744$, $p = 0.015$; Table 1). Proximity had the best usability score (M = 3.59, SE = 0.19), followed by Prediction (M = 3.50, SE = 0.19), Entropy (M = 3.30, SE = 0.19), and then Control (M = 2.92, SE = 0.19; Fig. 3). Tukey's HSD Test found that the mean usability rating was significantly different between Control and Proximity ($p < 0.05$, 95% C.I. = [0.096, 1.237]) as well as Control and Prediction ($p < 0.05$, 95% C.I. = [0.005, 1.146]). These results indicate that the participants seemed to prefer gaze-based acknowledgement, and the three methods were indistinguishable in subjective ratings.

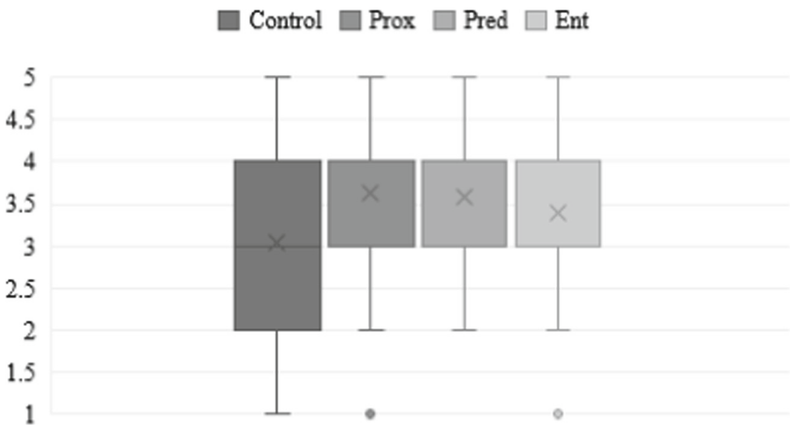

Fig. 3. Box plot of usability ratings across gaze-based acknowledgement methods.

Table 1. ANOVA of usability ratings across acknowledgement methods

Source	DF	Adj SS	Adj MS	F-value	P-value
Acknowledgement method	3	17.31	5.77	8.09	0.000
Participant	21	100.80	4.79	6.72	0.000
Error	239	170.44	0.71		
Total	263	288.33			

4 Conclusion

Alarm management could benefit from filtering alarms based on a real-time measurement of operator monitoring behaviors. Alarms anticipated by operators may become nuisance because the alarm cannot provide any new information. We investigated gaze-based acknowledgement designs intended to acknowledge and reduce the salience of anticipated alarms without any additional alarm management tasks. The usability ratings from the empirical study suggest that gaze-based acknowledgement could be a useful alarm management approach. More analysis will be conducted to determine whether gaze-based acknowledgement reduces distraction from on-going tasks and how well the gaze-based acknowledgement matches explicit alarm prediction.

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