Journal of Loss Prevention in the Process Industries 42 (2016) 35–46

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: www.elsevier.com/locate/jlp

Towards predicting human error: Eye gaze analysis for identification of cognitive steps performed by control room operators

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ARTICLE INFO

Article history:
Received 6 May 2015
Received in revised form
26 June 2015
Accepted 6 July 2015
Available online 11 July 2015

Keywords:
Process safety
Human error
Eye tracking
Cognitive engineering

ABSTRACT

Today's plants use highly reliable equipment, state-of-the-art automation and control, and deploy sophisticated safety management regimes so as to make accidents rare. Despite these measures, a number of recent accidents point to the continued need to improve process safety. Various studies indicate that more than 70% of the accidents in process industries originate from human errors. Traditionally, human reliability is accounted for by using Human Error Probabilities, which emphasizes inevitability. In this work, we demonstrate that eye tracking serves as a reliable sensor of various cognitive tasks performed by the operator while managing process abnormalities. Experimental studies conducted on 11 participants reveal characteristic fixation patterns that contain information about their cognitive ability to orient, diagnose and execute recovery actions during abnormal situations. These results hold promise for predicting incipient cognitive failures which in turn would enable proactive measures to prevent human error.

1. Introduction

Accidents in process plants often lead to large losses. Abnormal events arising from process upsets and production accidents result in 100 million USD yearly losses even in a medium-sized petrochemical company. This estimate does not even account for the colossal damages from tragic accidents like Bhopal gas disaster (1984), the fire at the oil storage facilities in Buncefield, UK (2005) and Jaipur (2009), Chevron's Richmond refinery fire (2012), and explosion at the fertilizer storage and distribution facility at West, TX (2013). In the last two decades both governments and industry around the world have made numerous interventions to improve process safety. Consequently, nowadays process plants regularly use highly reliable equipment with modern automation and control strategies along with numerous layers of protection. Despite these measures, the spate of accidents has not been stemmed – by one measure, 25% of the accidents that led to largest losses in the hydrocarbon industry over a period of 40 years have happened in the last 5 years from 2009 (Marsh, 2014). Thus, process safety continues to be one of the most important concerns for the chemical industry.

Analyses of various incidents indicate human errors as a primary cause for more than 70% of accidents in the recent past (Leveson, 2004). Operator errors viz. slips, lapses, mistakes, violations in a process plant are often cited as reasons for equipment outage, plant shutdown and various production accidents (Kidam et al., 2010). Increase in complexity of the processes, tight energy integration, recycles, presence of advanced control strategies, reduction in number of staffs without an effort to increase their cognitive skills in handling abnormal situations are some of the primary causes for human errors in process industries.

The traditional approach has been to look at human error as the initiating event of incidents using likelihood approaches, similar to the way that a piece of hardware is expected to fail at some frequency. Human errors have been understood using a set of Human Error probabilities (Munger et al., 1962) which was later extended to cover task/environmental variables along with human-engineering-design characteristics (Swain, 1990). In this approach, Performance Shaping Factors are used to consider contextual factors (Rasmussen, 1997). Hollnagel (1998) extended this by incorporating the various levels of control that an operator

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http://dx.doi.org/10.1016/j.jlp.2015.07.001
0950-4230/

has in a given context so as to make the reliability measure specific to a particular context. Chang and Mosleh (2007) proposed incorporating cognitive processes such as information processing, diagnosis and execution; this can however be only applied in simulation. Attempts have also been made to predict human error probabilities using expert judgment wherein a panel of experts in a specific domain (e.g. offshore oil and gas industry; maintenance procedures) provide information regarding the weights of the various performance shaping factors, which are then utilized to determine the human error probabilities (DiMattia et al., 2005; Deacon et al., 2010). These approaches thus rely on subjective estimates rather than sensing and measurement of the cognitive behaviors, which is the focus of this work.

In a typical control room, the cognitive tasks performed by an operator during an abnormal situation can be categorized into orientation, diagnosis and execution steps (Adhitya et al., 2014). For instance, when an abnormality occurs, the operator's attention is directed towards real-time data and information gathering from the process, its control system, alarm system, and/or support systems. In this task, the operator mentally orients to the current state of the process. Once adequate data has been obtained, the operator performs the diagnosis task by using mental models to hypothesize a set of possible causes that would explain the observed symptoms and identify the possible root cause of the abnormal situation. Next, based on this belief, the operator performs the execution task of taking corrective control actions to restore the process to normal operating conditions or at least bring it to a safe state. Depending on the outcome, all three tasks may be repeated until the real abnormality is isolated, and the process brought back under control. Human error could occur in the orientation, diagnosis, or execution steps, all with disastrous consequences. Thus automated monitoring to ensure that the operator is correctly performing the tasks will reduce human errors and hence accidents.

Recent advancements such as eye tracking, Electroencephalography (EEG), functional Near Infrared (fNIR) imaging, and Galvanic Skin Response (GSR) offer new tools for cognitive engineering – an emerging research field that analyzes the mental processes of the human actor such as perception, memory, reasoning, and motor response especially in the context of their interactions with other elements of a system. The eye tracker is appropriate to monitor the cognitive state of plant operators since it is non-invasive and is relatively simple to install and use (Matos, 2010). Studies in safety critical domains such as aviation and healthcare indicate that eye tracking throws light on the cognitive behavior of the human operator that could be utilized to develop cognitive models, evaluate the performance of human personnel, understand their emotional states and develop measures to improve the overall safety.

In this work, we demonstrate that eye tracking can act as a reliable sensor for identification of various cognitive tasks performed by the operator during process abnormalities. Results from our experimental studies demonstrate the efficacy of eye tracking measures in sensing the cognitive state of operators with a clear indication that eye gaze measurements help understand the control room operator's competence in performing orientation, diagnosis, and execution steps, especially during abnormal situations. Information about the cognitive state from eye tracking can help develop online performance assessment tool for operators indicating their lack of orientation, diagnosis, or inappropriate execution during disturbances or abnormal situations. The rest of this article is organized as follows. Section 2 presents a review of the existing literature on various attempts employing eye tracking measures to infer the cognitive behavior of human operators in various domains. The experimental setup and methodology used in our work is described in Section 3. Results obtained from application of eye tracking measures in our experimental studies are presented in Section 4. These results indicate the potency of eye tracking as a sensor for identification of cognitive tasks performed by control room operators.

2. Literature review

Javal, in 1878, discovered (as cited by Wade and Tatler, 2009) that eye movement while reading made a series of discrete pauses separated by jumps. These discrete pauses during eye movement are called fixations and the jumps are called saccades. Visual information processing is assumed to take place during fixations, whereas vision is essentially suppressed during saccades. Jacob (1993) suggested that saccades are fast and there is only a 100–300 ms delay between the onset of a stimulus and the resulting saccade. He suggested that saccades take approximately 30–120 ms and traverse a range between 1 and 40° of visual angle after which a 200–600 ms period of relative stability, called fixation, occurs. A set of fixations and saccades obtained from a participant viewing a process schematic during an experiment is shown in Fig. 1. The circles in the figure represent the fixation points with the size of the circle indicating the length of the fixation while the lines connecting the fixations denote the saccades. Bulling et al. (2009) suggested that the overall eye activity can be assumed to be a combination of fixations, saccades and blinks during which the eye pupil size could dilate, constrict, or remain unchanged.

Eye activity can be measured using an eye tracker with instances of its usage in various fields (Russo and Rosen, 1975; Russo, 1978; Lohse and Johnson, 1996). With recent technological advancements, eye activity can be measured using commercially available, non-intrusive, and accurate eye trackers from companies such as Tobii, SR research, and SMI systems eye tracker (Hermens et al., 2013). Typically, an eye tracking device detects (Ross, 2009) where a person's fovea, a small spot on the retina that is responsible for fine vision, fixates and the movement between fixations. Most commercial eye trackers employ an infrared light source directed towards the eye and the reflections from the eyes are recorded by a camera which is then processed to obtain information about the pupil size, fixation, and saccades. This technique of eye tracking is known as Pupil Center Corneal Reflection (Tobii Technology, 2010). A schematic of the typical setup is shown in Fig. 2. The sampling frequency of the eye tracker, i.e., the number of images acquired and processed per second, today range from about 20 Hz to 2000 Hz. Most of the studies that use non-invasive eye tracking methods follow a nine point calibration in which the participant is asked to look at a red dot (in the web version) that appears at selected nine points on the screen to determine the accuracy of data before conducting experiments.

In order to gain insights into the cognitive processes associated with a person's activity, the eye tracker data need to be analyzed using various statistical and computational techniques to derive insights into higher level processes of attention and comprehension (Ross, 2009). For example, a participant may fixate on a particular Area of Interest (AOI) for a longer duration but visit another AOI several times with short fixations each time. A detailed analysis is required to understand the significance of each AOI and its relevance to the problem addressed. There are several such measures that can be computed from the eye tracking data such as:

- Fixation duration: duration of each individual fixation within an AOI
- Fixation Count: the number of times the participant fixates on an AOI
- Dwell duration: duration of all visits within an AOI