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The explosion at institute: Modeling and analyzing the situation awareness factor

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ABSTRACT

In 2008 a runaway chemical reaction caused an explosion at a methomyl unit in West Virginia, USA, killing two employees, injuring eight people, evacuating more than 40,000 residents adjacent to the facility, disrupting traffic on a nearby highway and causing significant business loss and interruption. Although the accident was formally investigated, the role of the situation awareness (SA) factor, i.e., a correct understanding of the situation, and appropriate models to maintain SA, remain unexplained. This paper extracts details of abnormal situations within the methomyl unit and models them into a situational network using dynamic Bayesian networks. A fuzzy logic system is used to resemble the operator's thinking when confronted with these abnormal situations. The combined situational network and fuzzy logic system make it possible for the operator to assess such situations dynamically to achieve accurate SA. The findings show that the proposed structure provides a useful graphical model that facilitates the inclusion of prior background knowledge and the updating of this knowledge when new information is available from monitoring systems.

1. Introduction

On Thursday 28 August 2008 a runaway chemical reaction occurred at a methomyl production facility in Institute, West Virginia, USA. Highly flammable solvent sprayed from a 4500 gallon pressure vessel known as a residue treater and immediately ignited, killing two employees and injuring eight firefighters and contractors. The intense fire burned for more than four hours, more than 40,000 residents were evacuated to shelter-in-place for over three hours, and the highway was closed for hours because of smoke disruption to traffic. The Chemical Safety Board (CSB) investigation team determined that the runaway chemical reaction and loss of containment of the flammable and toxic chemicals was the result of deviation from the written start-up procedures and included the bypassing of critical safety devices intended to prevent such a condition occurring. A poor process mimic screen, which could not provide adequate situation awareness (SA) for the board operator, was another important contributing factor (CSB, 2011). The tragic event at Institute is an example of the difficulties experienced with regard to loss of SA, poor SA or lack of SA, all of which are now popular terms in accident investigation reports. However, SA itself is not the only cause of accidents (Dekker, 2013). In the case of the Texas City, TX BP Amoco Refinery explosion on 23 March 2005, in which 15 workers were killed and 170 injured, several failed control instrumentation and alarms caused an overfilled and over-pressurized tower to discharge a large quantity of flammable liquid into the atmosphere, while the control room operator could not maintain accurate SA when monitoring this complex, fast moving environment, and an ignition created one of the worst industrial disasters in recent US history (Pridmore, 2007).

A situation is a set of circumstances in which a number of objects may have relationships with one another and the environment, and situation awareness (SA) is knowing and understanding what is going on around you and predicting how things will change (Vincenzi et al., 2004). To date, several SA models, such as Endsley (1995), Bedny and Meister (1999), and Adams et al. (1995) have been developed; however, Endsley's model has undoubtedly received the most attention. This three-level model describes SA as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" (Endsley, 1995). The three-level model describes SA as an internally held product, comprising three hierarchical levels (i.e., perception, comprehension, and projection), that is separate from the processes called

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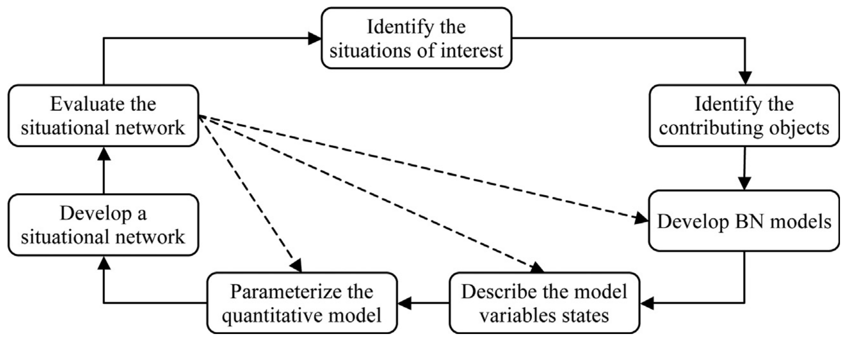

Fig. 1. A cycle to build a situational network using BNs.

situation assessment used to achieve it (Endsley, 1995). In fact, situation assessment models explain the main features and general principles about how people process information and interact with the environment to maintain their SA. The primary research into SA came from the aviation industry, when a review of aircraft accidents showed that poor SA was the main causal factor. It was also found that most of the errors occurred when data were unavailable or difficult to discriminate or detect (level 1). About 20% of errors involved lack of, or an incomplete mental model, use of an incorrect mental model, over-reliance on default values, and miscellaneous other factors (level 2). In addition, around 3.5% of errors involved over-projection of current trends or miscellaneous other factors (level 3). Another review in offshore drilling accidents by Sneddon et al. (2013) showed that 40% of such accidents are related to SA, and the majority of those SA errors (67%) occurred at the perceptual level, 20% concerned comprehension, and 13% arose during projection. Therefore, this is not a problem limited to aviation, but one faced by many complex systems when combining and presenting the vast amounts of data available from many technological systems in order to provide true SA is a challenge.

In complex systems, SA level 1 is highly supported through the various heterogeneous sensors and appropriate signal-processing methods to extract as much information as possible about the dynamic environment and its elements, but regarding SA levels 2 and 3, there is still a need for appropriate and effective methods to support operators to infer real situations and to project their status in the near future (Fischer et al., 2011; Jones et al., 2011). In maritime security, an automated system has been developed that has the ability to recognize any deviance from normal behavior (Van Den Broek et al., 2011). In military services, there are several SA systems, such as Ghanea-Hercock et al. (2007) and Smart et al. (2007), that are able to collect, filter and present different sources of data, and also support some form of low-level data fusion and analysis. However, these systems are not able to provide a deep, semantic modeling of the domain and are consequently unable to generate conclusions. Their users have to integrate information by themselves to assess and project a future situation, so a system architecture has been developed by Baader et al. (2009) that focuses on using formal logic and an automated theorem to build an SA system in a more useful way. In the force protection domain, Brannon et al. (2009) used machine learning techniques to project a threat index. They took into account various inputs such as binary, categorical, and real-valued data to generate attributes including confidence levels, as well as evidence in support of, or against the assessment. In the aviation domain, an SA system called the tactile situation awareness system (TSAS) has been developed by Kim and Hoffmann (2003) to improve the SA of pilots in simulated rotorcraft under high-load working conditions. Rather than presenting visual or aural information for the efficient delivery of SA, this system relies on a wearable suit equipped with a tactile device that provides an intuitive human computer interface with three-dimensional space. In the domain of nuclear power plants, Kim and Seong (2006) proposed a computational model of situation assessment that projects the states of the environment probabilistically when receiving information from indicators. Fischer and Beyerer (2012) also applied automated projection in surveillance systems where situations of interest in the maritime domain are recognized by calculating probabilities for the situations, given evidence obtained from observable characteristics. Although the application of SA systems is not limited to the above domains, its application in safety-critical environments such as process control is very rare. Most prior system safety studies in these environments focus on the deviation of the process from an acceptable range of operation. Therefore, in the development of operator support systems, the use of quantitative knowledge and hardware failures has been relied on significantly. Most of these research studies focus on the identification of operation faults (Qian et al., 2008) or the prediction of process variables (Juricek et al., 2001) that will violate an emergency limit in the future; however, further research showed that when faults occur, human operators have to rely on their experience under working pressure to understand what is going on and to contribute a solution (Klashner and Sabet, 2007). When an abnormal situation occurs in a safety-critical system, operators firstly recognize it by receiving an alarm, and secondly need to understand what is happening in the plant by situation assessment. During the situation assessment process, operators receive information from observable variables or other operators and process the information to establish situation models based on their mental models (Kim and Seong, 2006).

This study aims to introduce a methodology to model and analyze the SA factor in abnormal situations that can be utilized in the development of operator support systems. To identify abnormal situations, this paper uses risk indicators. Therefore, when a hazardous situation is defined as a possible circumstance immediately before harm is produced by the hazard, an abnormal situation is defined as a hazardous situation if its risk is not acceptable. This definition can also help operators to understand the hierarchy of investigations (i.e., a situation with a higher risk has priority over other situations to be investigated). The paper uses Bayesian networks to model situation models based on a control room operator's mental models, and it also relies on risk level projections

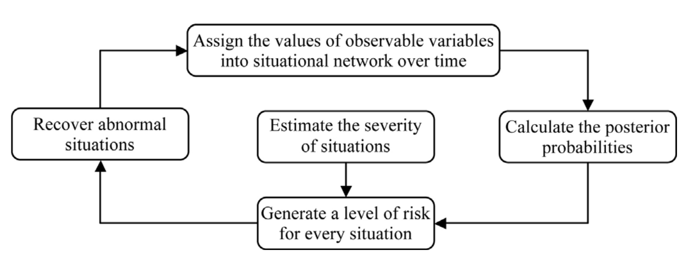

Fig. 2. A cycle to analyze the situational network over time.