Improving safety and performance in high-risk industries: an approach to human factors analysis through wearable devices

Plínio Ramos[a*], Caio Souto Maior[b], Isis Lins[a], Marcio Moura[a]
[a] Universidade Federal de Pernambuco, Recife, Brazil
[b]Universidade Federal de Pernambuco - CAA, Caruaru, Brazil

Abstract: Accidents in the energy industries can have devastating consequences, affecting individuals, entire communities and the environment. Accident prevention plays a crucial role in protecting lives, requiring the implementation of preventive measures and adherence to safety protocols. In high-risk industries such as oil and gas, accident prevention is particularly vital due to hazardous operations such as drilling, refining, transportation and storage of volatile substances. Simultaneously, human factors are essential for process safety management systems, especially in complex processes that expose workers to physical and psychosocial stressors. In fact, accidents such as the 2001 P-36 platform accident in Brazil underscore the direct link between the emergency response activities of human operators and deaths resulting from the ignition of gas clouds during efforts to regain control. In this context, factors that influence emergency response, such as operators' stress and fatigue levels, can be assessed through biological signals (for example, electroencephalogram - EEG, electromyogram - EMG and electrocardiogram - ECG). Therefore, this study aims to collect and analyze biological data within a simulation of various accident scenarios in a realistic refinery environment using virtual reality (VR). The simulation incorporates visual and audio elements alongside the recording of physiological signals, aiming to support emergency response teams' decisions and serve as a complementary training tool for these teams. The simulation collects physiological data through wearables (EEG, ECG, EMG) for use in a machine learning model capable of detecting physiological changes of the emergency response team and gaining insights into emotional states, communication, situational awareness, readiness, and decision-making. The proposed study offers a perspective for improving the detection of anomalies in biological signals that reflect robustness, thereby increasing safety and performance in real-world applications. This research positively impacts the oil industry, providing a solution to accident prevention, challenges related to human factors and automation in crucial industrial safety systems without exposing participants to real-world risks.

Keywords: Accident Prevention, Human Factors Analysis, Wearable Devices, Industrial Safety Systems.

1. INTRODUCTION

Accidents in the energy industries, particularly in the oil and gas sector, have long been a significant concern due to their potential for catastrophic consequences. In high-risk sectors, operations involving drilling, refining, transporting, and storing volatile substances are inherently hazardous. Fugitive emissions from the operations of these industries pose additional risks. These emissions arise from equipment leaks and irregular operations (Zhang et al., 2022). For example, pipelines, a common system for storing and transporting petroleum products, are particularly susceptible to leaks due to various factors, including structural defects, erosion, and human factors (Spandonidis et al., 2022). Such leaks not only contribute to environmental pollution but also pose significant risks to human lives (Khodadadi-Mousiri et al., 2023).

Workers in these environments face numerous physical and psychosocial stressors that can impair their performance and increase the likelihood of accidents. Historical incidents, such as the 2001 P-36 platform accident in Brazil, illustrate the crucial role of human operators during emergencies. The ignition of gas clouds during attempts to regain control led to fatalities, highlighting the direct impact of human emergency response activities on safety outcomes (Almeida & Vinnem, 2020).

In cases like these, the emergency brigade receives training to quickly respond to the accident site. The brigade's training, preparation and ability to collaborate with other emergency response entities are crucial to effectively manage the situation and minimize the impact of the accident (Shojaei et al., 2023). Effective management of human stress and fatigue during crises is essential to preventing other tragedies.

Technological advancements have opened new avenues for enhancing safety measures, particularly through the use of biological signals to assess the condition of workers. Monitoring biological data, such as electroencephalogram (EEG), electromyogram (EMG), and electrocardiogram (ECG), provides valuable insights into the physiological and psychological states of individuals (Choi et al., 2023; Jafari et al., 2023; Qi et al., 2018). This real-time data can inform decision-making and training, improving safety by detecting stress, fatigue, and other factors that affect performance during emergency responses.

This study aims to leverage these technological advancements by collecting and analyzing biological data within a simulated refinery environment using virtual reality (VR). By integrating visual and audio elements with the recording of physiological signals, the simulation provides a realistic and immersive training tool for emergency response teams. The collected data will be used in a machine learning model to detect physiological changes, thereby gaining insights into the emotional states, communication effectiveness, situational awareness, readiness, and decision-making capabilities of the participants.

2. THEORETICAL BACKGROUND

2.1. The Role of Human Factors in Process Safety Management

Human factors are one of the main causes leading to accidents. For example, research shows that 70% to 80% of aviation accidents, 60% of petrochemical accidents, 90% of steel and metallurgy accidents, and 90% of traffic accidents are caused by human factors (Yalcin et al., 2023). Specific reports from the petroleum industry consistently reiterate this finding over the years, that human factors are the main causes of accidents (Zarei et al., 2023).

Simultaneously, it is crucial to consider regulatory initiatives, such as those established by the National Agency of Petroleum, Natural Gas, and Biofuels (ANP) in Resolutions No. 43 of 12/06/2017 and No. 5 of 01/29/2014, which play a fundamental role in the Operational Safety Management System (SGSO) of the oil and gas industry in Brazil (ANP, 2023). Through the SGSO, the ANP emphasizes the importance of human factors in risk analysis, highlighting them as an integral part of risk management. The most recent approach to the ANP's SGSO explicitly recognizes the relevance of human factors, emphasizing the need to consider organizational, environmental, technological, and individual elements that influence behavior in the workplace and can affect health and safety.

In this context, considering human factors becomes crucial in managing the safety of complex processes, where workers indeed face a series of physical and psychosocial challenges (Omidi et al., 2018; Tong et al., 2022). These challenges in the oil and gas industry include exposure to noise, vibration, intense workloads, hazardous operations, and stringent safety regulations (Parkes, 2012), which induce stress in operators and can be monitored through electrophysiological methods.

2.2. Utilizing Biological Signals for Assessment

The distinction between different stress states can be perceived through neurological and muscular changes in the subject (Li et al., 2015). With the advancement of technology and cost reduction, wearable sensory devices have become accessible, allowing people to collect useful information for various purposes in their daily lives. EEG, for example, is an electrophysiological technique used to record the electrical activity originating in the human brain. This procedure typically involves using a specialized device, where the essential components consist of unique metal plate electrodes positioned on the human scalp (Dzedzickis et al., 2020; Lins et al., 2024). The brain's responses to various stimuli are commonly measured through EEG signals, which are then categorized into five frequency bands: delta, theta, alpha, beta, and gamma (Ramos et al., 2022).

Additionally, ECG and EMG are other electrophysiological monitoring methods that play a crucial role in investigating stress levels. ECG is a technique that records the heart's electrical activity over time. Variations in heart patterns can offer insights into an individual's physiological state, including moments of stress and fatigue (Shiwu et al., 2011). Changes in heart rates, heart rate variability, and other cardiac parameters can indicate transitions between different states (Benezeth et al., 2018).

EMG, in turn, measures the electrical activity of muscles. Stress and fatigue can result in changes in muscle activity, as increased stress can influence muscle tonicity and the degree of relaxation in an individual. By analyzing muscle activity patterns in different body regions, researchers can identify signs of stress and determine its influence on neuromuscular systems (Qi et al., 2018).

In addition to stress and fatigue, EEG, ECG, and EMG can also be instrumental in assessing other cognitive and physiological states, such as Situational Awareness (SA)(Kang et al., 2024). For example, lack of SA is a significant source of human error in tasks involving complex decision-making under pressure. Advances in the literature illustrate the broader potential of using EEG, ECG, and EMG to also assess cognitive states such as SA, which are vital for maintaining safety and performance in high-risk environments.

2.3. Use of VR for Safety Training and Simulation

Workplace safety is a global concern, and proper training plays a crucial role in preventing accidents and reducing their impacts. Traditionally, safety training has followed a conventional approach, based on lectures, videos, and similar methods (Ebnali et al., 2021). However, evidence suggests that these methods can lead to rapid loss of attention and engagement among participants. As an alternative, the use of VR has emerged as a promising approach to make safety training more interactive and engaging.

The study by Chan et al. (2023), conducted a study within the chemical industry to evaluate the effectiveness of safety training by comparing traditional methods to the use of virtual reality (VR). Their findings revealed that VR training resulted in higher engagement and motivation among participants compared to conventional techniques. Nonetheless, they identified certain limitations, such as usability challenges and fatigue, underscoring the need to address these issues to enhance the effectiveness of VR training.

Another study (D'Amico et al., 2023) explored the effectiveness of combining serious games (SG) with non-immersive VR to improve evacuation behavior during urban floods. Their results showed that the integration of SG with non-immersive VR training substantially increased participants' knowledge and self-efficacy in flood disaster scenarios, suggesting a strong correlation between behaviors observed in VR and those in real-world situations.

Moreover, a systematic review by Scorgie et al. (2024) on the use of VR in safety training highlighted an increasing trend in VR adoption since 2013. The qualitative analysis and meta-analyses in this review demonstrated that VR training surpassed traditional methods in terms of knowledge acquisition and retention, while also offering a superior user experience. These findings highlight the need for further research into the factors that influence the effectiveness of VR training and emphasize the potential of VR technology to enhance workplace safety.

3. METHODS

3.1. Experiment Definition

The experiment involves an immersive game designed to replicate potential accidental scenarios of hazardous chemical leaks, set up to gather biological signal data (EEG, EMG, ECG) using wearable devices. These biological signals from participants were used to train a machine learning algorithm aimed at identifying changes in biological patterns that might pose a risk to the operator and the emergency brigade's activities.

Set within an oil refinery, the immersive game focuses on accidents involving a naphtha hydrotreating subsystem. The leak point is specifically located between the recycle pumps and the heat exchangers. In industrial settings, uncontrolled releases of flammable and toxic materials can lead to disastrous incidents such as explosions and fires. When an accident alert is triggered, the emergency brigade must respond swiftly to control the release and prevent it from worsening. Consequently, once the alert is received, the emergency brigade must proceed to the designated leak point. Upon arrival, their tasks include controlling the leak, avoiding areas with high concentrations of hazardous materials, and ensuring that no potential ignition sources are present. The leak point will be randomly selected and communicated to the player, as illustrated in Figure 1.

Figure 1. Example of gas leakage in a refinery on VR

The selected scenario was designed to simulate high-stakes decision-making, and the rapid response required during a real-life industrial accident. The scenario is expected to induce stress and fatigue by placing participants in a situation where they must quickly interpret critical information, navigate a hazardous environment, and make timely decisions under pressure. The unpredictability of the leak point, coupled with the urgency to avoid potential explosions and fires, is intended to heighten participants' cognitive load and emotional arousal, thereby simulating the stress experienced during actual emergency response operations. This design aims to trigger physiological responses that can be measured through biological signals.

3.2. Experiment Setup

The data collection procedure begins immediately after the participant's setup and training time. This study involved 5 participants selected from the Laboratory of Risk Analysis, all of whom were familiar with oil and gas processes, as well as virtual reality (VR) tools, due to their academic background and ongoing projects in related fields. This simulation takes around 10 minutes, with participants being previously asked not to consume any coffee, energy drinks, or other stimulants for at least 12 hours prior to the simulation.

Before the start of the simulation, participants underwent a brief training session to familiarize themselves with the VR tools and the emergency procedures simulated within the game. During the simulation, participants remained seated to maintain consistent conditions and reduce variability in the collected data due to physical movement.

During the simulation, the game character is an emergency brigade member who notices the leak alert and must take all necessary actions to control the accidental scenario under controlled physical and emotional conditions (monitored biological signals) and at the appropriate time. The character needs to control the leak within the specified time and avoid high concentration regions, as well as perform the following actions:

1. Read a message indicating a leak point;
2. Go to the leak point within a specified time;
3. Close the valves to stop the flow of naphtha.

The game should display the leak point, material concentration in the environment, and wind direction to the player. At the end of the VR simulation, participants will be asked to complete self-assessments through questionnaires that allow for the subjective evaluation of situational awareness and cognitive demand levels. This study was conducted following ethical guidelines and was approved by the Ethics Committee under the approval number 77704224.7.0000.5208, with all participants providing written informed consent prior to their involvement. At the operational level, the simulation is set up as follows.

3.3. Monitoring Biological Parameters

Inducing emotions in a laboratory environment should include plausible enough stimuli (sounds, images) to induce an intensified level of physiological stress, such as feelings of nervousness or anxiety. Thus, these stimuli can be interpreted in physiological signals and recognized by existing associated methods. EEG data are collected through a dedicated device. The area where the EEG electrodes are placed is prepared, including parting the hair and cleaning the scalp to remove any residue of creams or oils.

EMG electrodes are specifically placed on the trapezius muscle to assess participants' relaxation and stress states. The area is prepared, including cleaning the skin to remove any residue of creams, oils, or dirt. Before the experiment begins, a brief conduction test should be conducted to ensure that the electrodes are properly attached and the signal quality is satisfactory for both EEG and EMG. During the installation of the ECG, the heart rate monitor is carefully positioned in direct contact with the skin, located just below the sternum for an accurate reading of cardiac signals. To ensure a robust connection between the chest and the transmitter, the electrodes on the back of the monitor are moistened before application. Additionally, Bluetooth pairing allows participants to connect the heart rate monitor to compatible devices, facilitating data collection and offering greater freedom of movement to participants.

For the experiment, the laboratory provides the following equipment:

- EEG headsets for electroencephalography - EMOTIV INSIGHT is designed for scalable and contextual research on the human brain and provides access to professional-level brain data with a quick and easy-to-use design, setup in around 2 minutes, saline-based electrodes without the need for conductive gel, wireless connection, 20-hour rechargeable battery;
- Garmin® HRM-Pro Plus Chest Heart Rate Monitor for heart rate monitoring. Through ANT+® technology and BLUETOOTH® Low Energy technology, this dual-transmission monitor transmits accurate real-time performance and heart rate data to smartwatches and computers and other applications;
- 2-channel EMG module, which includes an analog acquisition circuit and a digital signal filtering process. The front acquisition circuit collects muscle electrical signals through two EMG channels. We use a single-chip microcomputer for digital filtering processing, and muscle electrical energy values are collected for processing to obtain power. We then send the muscle electricity power value, the average muscle electricity value, the collected muscle electricity value, and the muscle force value via Bluetooth 4.0.

3.4. Machine Learning for Analysis

To analyze the collected biological signal data (EEG, EMG, ECG), we have chosen to use a Multilayer Perceptron (MLP) model, implemented with the scikit-learn library in Python (Pedregosa et al., 2011). The MLP is a type of artificial neural network well-suited for classification tasks due to its ability to capture complex patterns in data through multiple layers of neurons (Ramos et al., 2022).

The physiological changes detected in the participants are used to infer several key aspects of their performance during the simulation. Specifically, emotional state: changes in EEG signals and the increased heart rate variability are indicative of stress levels and emotional arousal; communication effectiveness: EMG signals can reflect tension or relaxation, which may correlate with the participant's communication effectiveness during the simulation; and SA: EEG data can be used to assess cognitive workload and attention, which are critical components of SA.

By leveraging the power of machine learning, we aim to enhance the detection and prediction of hazardous situations based on these physiological responses. This approach allows us to gain a comprehensive understanding of how different aspects of human performance, such as emotional state and SA, are influenced by stress and fatigue during emergency scenarios.

4. RESULTS AND CONCLUSION

In this experiment, we utilized three types of recordings to analyze the effectiveness of wearable devices in detecting biological patterns during simulated emergency scenarios. The recordings included EEG, EMG, and ECG signals, collected from a participant during a simulation of hazardous chemical leaks at an oil refinery. The variability of the heart rate, measured by the Garmin® HRM-Pro Plus chest heart rate monitor, was minimal, suggesting that the physiological response captured by this device was consistent and did not exhibit significant variations.

Three separate recordings were conducted, and the results were consistent across all attempts. The analysis presented here reflects the best result obtained from one participant, demonstrating the capability of the devices to capture and identify relevant biological patterns. The MLP models were trained to classify the biological data into two states: "Stress" and "Rest." The confusion matrices for each type of signal were manually constructed and presented the following results (Figure 2).

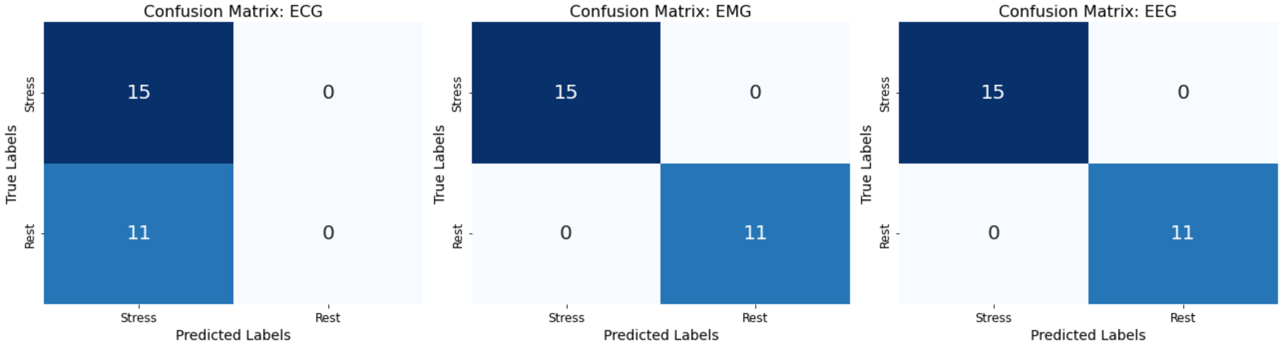

Figure 2. Confusion Matrix for ECG, EMG e EEG

The results of the confusion matrices indicate that the MLP model performed perfectly in classifying the EMG and EEG signals, with all predictions correct for both states. However, for the ECG signals, the model struggled to correctly classify the "Rest" state, indicating limited variability in the heart rate measured by the chest strap.

This limited variability suggests that while the heart rate monitor is effective at measuring real-time heart rate, it may not capture subtle variations that differentiate "Stress" and "Rest" states as clearly as EMG and EEG signals do. EMG and EEG data shows significantly higher activity of brain and muscle during game conditions, suggesting increased physical effort and stress. ECG data suggests a consistent heart rate response with minimal variability, highlighting the need to integrate multiple physiological signals for a comprehensive assessment.

The results highlight the importance of using a combination of different types of biological signals to obtain a comprehensive assessment of physiological responses during emergency scenarios. The consistent performance across recordings reinforces the validity of the results and the capability of the devices to provide reliable data for biological pattern analysis.

5. CONCLUSION

The integration of wearable devices for collecting physiological data (EEG, EMG, ECG) and analyzing it through machine learning models has shown significant promise in distinguishing different states (stress vs. rest) in simulated emergency scenarios. The limited variability in ECG signals suggests the need to enhance the sensitivity of heart rate monitoring or combine it with other biological signals for a more comprehensive analysis. The use of EMG and EEG proved highly effective in differentiating the states, providing a valuable tool for improving operational safety in industrial environments.

Thus, emergency response training can be improved, ensuring that operators maintain optimal performance during critical situations. The use of VR simulations and real-time physiological monitoring offers a safe and effective training environment, reducing the risk of real-world accidents.

This research provides a novel perspective on enhancing safety and performance in the oil and gas industry. By focusing on the detection of physiological anomalies through wearables, the study aims to improve the robustness of emergency response systems. Ultimately, this approach contributes to accident prevention and addresses challenges related to human factors and automation in industrial safety systems, advancing overall safety and efficiency in the energy sector.

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