Digital Twin-Based Health Maps for Construction Worker Health Monitoring: Assessing Feasibility and Viability

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ABSTRACT

The construction industry is known for its disproportionately high fatality and injury rates, making it one of the most hazardous industries in the US. Despite the significant risks involved, there is a lack of effective health monitoring in construction jobsites. While wearable physiological sensing and artificial intelligence advancements have introduced unique opportunities to assess workers' health status, there are still inefficiencies in representing that information to support managers' decision-making. Recently, the concept of digital twin (DT) has been used in various construction applications. Given the exponential growth of its enabling technologies, DT has great potential to transform worker health monitoring in construction jobsites. Therefore, this research investigates the feasibility of integrating workers' physiological responses with DT technology to generate health maps that deliver workers' aggregated health information to managers to reinforce their decision-making. The DT-based health maps are expected to enhance workers' occupational health and safety at construction jobsites.

INTRODUCTION

The construction industry is one of the most hazardous industries in the U.S., triggering extensive physical and mental health challenges for field workers (Zhou et al. 2012). Nearly 40% of the construction workforce in the U.S. suffer from severe physical fatigue (Ricci et al. 2007). Further, about 70% of construction workers have reported experiencing excessive mental stress (Jebelli et al. 2019). Such physical and mental challenges can result in workplace injuries and undermine workforce safety and well-being. Therefore, it is necessary to effectively monitor and evaluate workers' health and safety conditions to mitigate work-related injuries and fatalities at construction jobsites.

Despite the significant health and safety risks for field workers, there is a lack of effective health-monitoring methods at construction jobsites. The majority of existing methods for assessing workers' physical and mental health status rely on self-assessment measures, such as the Borg Rating of Perceived Exertion questionnaire for physical fatigue measurement (Williams 2017) and the Occupational Stress Indicator questionnaire for mental stress measurement (Evers et al. 2000). Nevertheless, due to the subjective and intrusive nature of these techniques, applying them in the field and achieving concrete results can be challenging (Rabeiy 2019). Thus, there is an increasing need for objective and continuous approaches to assessing workers' health status at construction jobsites.

Physiological responses to external stimuli can offer valuable information about the overall health status of an individual (Aryal et al. 2017). In this context, the advent of wearable biosensors and artificial intelligence (AI) has created unique opportunities to objectively and non-intrusively evaluate workers' health metrics in the field (Ahn et al. 2019). While these technologies allow continuous collection and interpretation of workers' health information, there is still a lack of representation methods to effectively deliver the information to safety managers to reinforce their decision-making and situational awareness. Given the notable growth of supporting technologies (e.g., big data, internet of things), the adoption of digital twin (DT) holds promise to effectively characterize a construction worker's health information in real-time through virtual representations of the construction jobsite.

To address the abovementioned limitations, this study aims to evaluate the feasibility and viability of integrating workers' physiological responses with DT technology to generate worker health maps of construction jobsites. To that end, workers' physiological data are acquired through wearable biosensors and interpreted using machine learning algorithms to distinguish their physical health status. The results are then paired with corresponding location data and represented through informative health maps. The generated maps can help managers promptly understand the health condition of the workforce. As such, the proposed DT-based health maps are expected to enhance workers' occupational health and safety at construction jobsites.

DIGITAL TWIN APPLICATIONS IN CONSTRUCTION

Digital Twin (DT) refers to a digital representation of a physical item or assembly created utilizing integrated simulations and service data (Vrabič et al. 2018). Over the past few years, DT has attracted particular attention in different sectors due to recent developments in big data, the Internet of Things (IoT), artificial intelligence, and sensor technologies (Liu et al. 2022). In the construction sector, DT is gradually being adopted for various applications, including facilities operations and maintenance (Zhao et al. 2022), infrastructure management (Al-Sehrawy et al. 2021), anomaly detection of the built environments (Lu et al. 2020), and supply chain management (Lee and Lee 2021). In addition, the application of building information modeling (BIM) has aided the adoption of DT at the design and engineering stage of construction projects (Opoku et al. 2021). In this regard, BIM can provide 3D communication for DT, and when combined with a wireless sensor network, it can create a real-time active model to provide designers with accurate information throughout the design stage of the project. Lastly, many studies have implemented the enabling technologies of DT, such as sensors and visualization technologies, for construction safety purposes, enabling managers to take appropriate preventive actions to diminish the risks of injuries and fatalities (Hou et al. 2020). Considering that health monitoring of the construction workforce requires large volumes of data generated from multiple resources, the proven capabilities of these technologies can be vital driving forces to adopt DT for real-time worker health monitoring at construction jobsites.

DIGITAL TWIN FOR CONSTRUCTION WORKFORCE HEALTH MONITORING

The construction sector is characterized by a dynamic and complex work environment, generating vast amounts of information for safety managers. Given that occupational risks are only present when workers are on-site, it is crucial for managers to have a proper understanding of the geographic location of workers on jobsites. In this regard, several positioning methods, such as the global positioning system (GPS), ultra-wideband (UWB) technology, and vision-based systems, have been used to track individuals on the jobsite (Park and Brilakis 2016). Combined with these technologies, DT has proven to be an effective solution for avoiding collisions and improving safety monitoring in the construction industry.

In addition to the location of workers, their actions and behaviors also play a significant role in accidents on jobsites. Consequently, identifying and preventing unsafe actions and behaviors of workers using the DT technology has become the focus of several construction worker health monitoring studies. Akanmu et al. (2020) proposed a DT framework for reducing musculoskeletal injuries among construction workers. By tracking the kinematics of workers' body segments and assessing their ergonomic exposures, the proposed framework could identify ergonomic risks and communicate them to workers via an augmented virtual replica within their field of view. Sharotry et al. (2020) also developed a DT framework for real-time analysis of an operator's movements during a manual material handling task. The framework was able to provide real-time feedback on proper lifting motions, enabling the evaluation of the risk of musculoskeletal disorders in manual material handling tasks.

METHODOLOGY

This study investigates the feasibility of developing DT-based health maps of construction jobsites to enhance construction workforce health monitoring. The framework connects the physical world entities (i.e., workers) and their attributes to the digital world using the Internet of Things (IoT) and biosensors to generate informative health maps of the workforce. The hazard hotspot locations and the aggregated health status of the workers can synchronously update the DT-based health maps to support managers' decision-making regarding the health and safety of the construction jobsite. Figure 1 shows the overall framework of the proposed methodology.

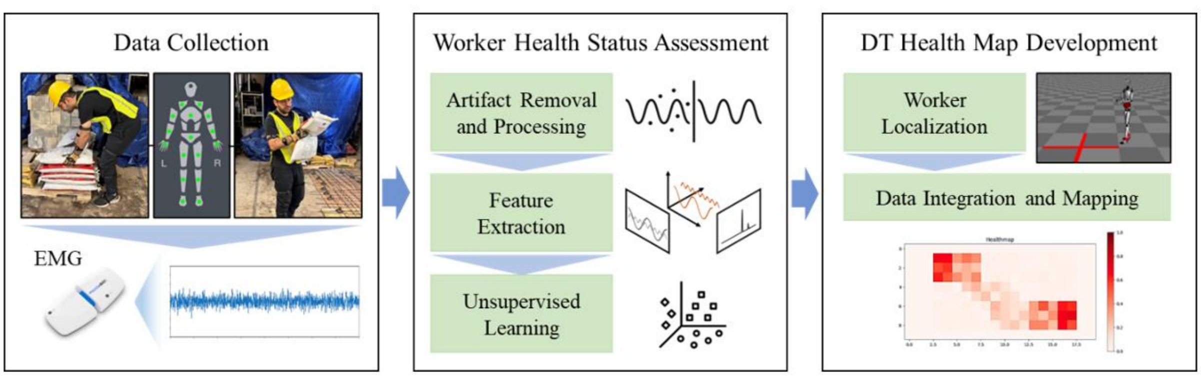


Figure 1. Overview of the proposed methodology

Data Collection. Previous research has shown the potential of physiological sensing methods for assessing various worker health parameters, including cognitive load (Liu et al. 2021), mental stress (Jebelli et al. 2018), and muscle fatigue (Jebelli and Lee 2019). In this study, physical stress on workers' back muscles was of particular interest due to its high prevalence among workers. Therefore, a material handling task in an indoor construction work environment was selected for worker physiological sensing and health map generation. The material handling task, which is a common task in the construction industry, involved repetitive motions and awkward postures that could lead to significant levels of physical stress on the workers. Six healthy subjects participated in this study. None of the participants had any mental or physical disorder that could adversely affect their task performance. The participants were equipped with a wearable EMG sensor that was attached to their back muscles using adhesive pads. They were also provided with a motion-capturing system for position tracking. During the task performance, the participants were asked to lift cement bags weighing 14 kg (30 lb.), carry them for 6 m (20 ft), and put them down repeatedly. Meanwhile, the EMG sensor continuously collected data at a rate of 1000 Hz, which were transferred to a nearby computer in real-time. The material handling task could last about 3 minutes, during which participants performed multiple rounds of lifting, carrying, and placing heavy bags. Figure 2 shows the data collection procedure and equipment.

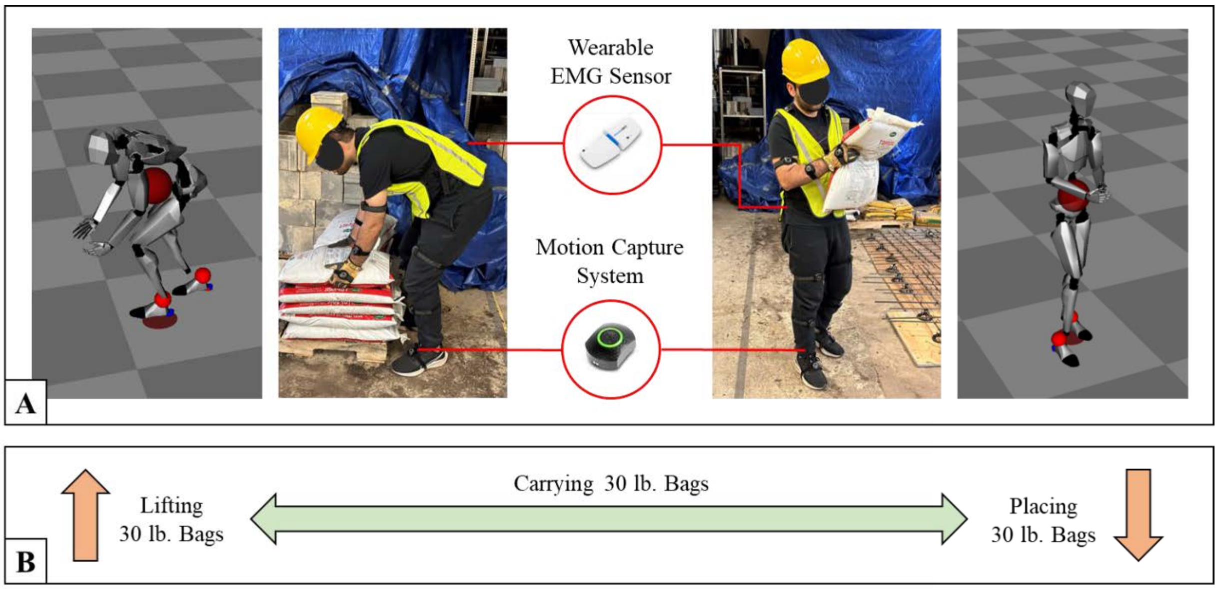


Figure 2. Data collection procedure and equipment, (A) subject lifting material bags (left side) and carrying them (right side), (B) different steps of the proposed material handling task, namely lifting, carrying, and placing 30 lb. bags.

Worker Health Status Assessment. To assess workers' health status (i.e., physical stress on their back), the electrical activity of the back muscles was measured using an Electromyography (EMG) sensor. The EMG sensor provides valuable information about muscle contraction and relaxation and can help identify physical stress on a worker during construction activities. Since the recorded EMG signals were contaminated with noises from sources other than muscle activity, the authors applied various filtering methods, including a bandpass filter and a Hampel filter, to acquire high-quality signals. More specifically, a bandpass filter with a lower cutoff frequency of 0.5 Hz and a higher cutoff frequency of 250 Hz was applied to reduce external signal artifacts. A Hampel filter was also used to eliminate signal outliers. Following the artifact removal, EMG signals were rectified and normalized relative to maximal voluntary contraction (MVC). The authors then extracted several features from processed signals in time and frequency domains to interpret the recorded EMG data. Accordingly, mean absolute value (MAV), root mean square (RMS), standard deviation (SD), zero crossing (ZC), mean frequency (MEF), and median frequency (MDF) were calculated from windows of EMG signals with different sizes.

Afterward, an unsupervised learning algorithm, i.e., k-means, was employed to group EMG data points into two clusters based on their similarities. The number of clusters was set to two (K = 2) because the selected construction task included lifting and putting down heavy items (high physical stress on back muscles) and carrying those items (low physical stress on back muscles). The k-means algorithm iteratively grouped EMG data based on the distance between data points and the center of the clusters. The objective function of the k-means can be represented as:

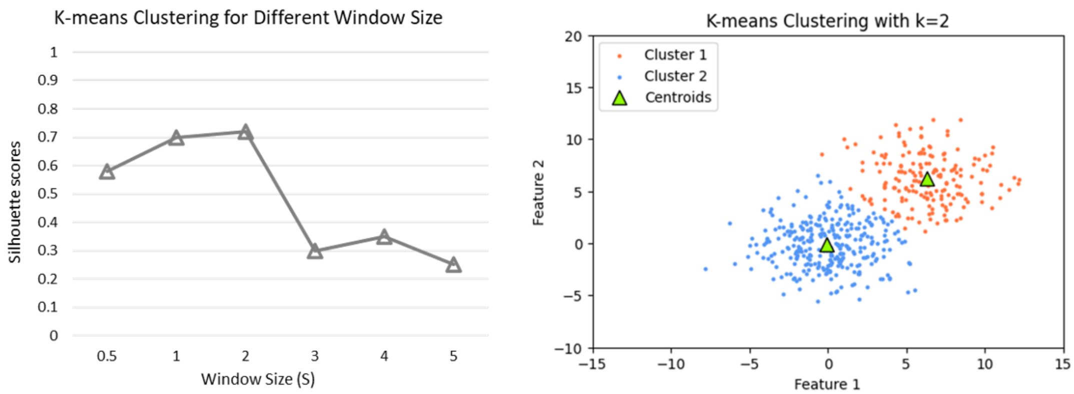
$$\underset{S}{argmin} \sum_{i=1}^{k} \sum_{x \in S_i} |x - \mu_i|^2 \tag{1}$$

Where k represents the number of clusters, $\boldsymbol{S}$ is the set of data points, and $\boldsymbol{\mu}$ is the centroid of each cluster. The algorithm was run for a maximum of 100 iterations, and the final clustering was chosen based on the minimum sum of squared distances between data points and their cluster centers.

Digital Twin-based Health Map Development. Collecting workers' location data is critical for creating a geospatial health map of a construction jobsite. This study employed an inertial measurement unit (IMU)-based motion-capturing system to collect indoor positioning data. IMU sensors can provide precise measurements of accelerations, angular velocities, and magnetic field strengths, which are essential for determining the orientation and motion of an individual in an indoor environment. By using a network of wearable IMU sensors, it is possible to collect real-time data on the position and orientation of workers, which can be used to create an indoor map of their locations. This data was transmitted wirelessly to a central computer or cloud-based platform, where it was processed. The location of the worker was extracted manually and integrated with the results of the clustering approach. Consequently, a script was developed to read the x-y coordinates and the corresponding labels and mark the location data pertinent to the high physical stress on a scatter plot. A heatmap was then overlaid at the top of the scatter plot, showing the frequency of the data points in each block. A color bar was also added to the heatmap to show the normalized values of the frequency scale, where 0 represents the minimum, and 1 represents the maximum frequency.

RESULTS AND DISCUSSION

In this study, the k-means clustering algorithm was employed to group EMG data into two clusters (K = 2). To that end, the EMG signals were segmented into windows of varying lengths, namely 0.5 s, 1 s, 2 s, 3 s, 4 s, and 5 s, and features were extracted from each window using the procedures described earlier. The results showed that the optimal window size for the clustering algorithm was 2 s, which yielded the highest Silhouette score of 0.72 (Figure 3-A). This indicates that the data points within the clusters were more similar to each other than to those in the other cluster, demonstrating good cluster separation. In contrast, the Silhouette score decreased with smaller or larger window sizes. The weaker performance may be due to the loss of important information with shorter windows or the introduction of irrelevant information with longer windows, resulting in decreased cluster separation and increased overlap between clusters. Figure 3-B also shows the scatter plot of the EMG feature space, where the orange and blue points represent the data points belonging to cluster 1 (high physical stress) and cluster 2 (low physical stress), respectively. These results suggest that the k-means clustering algorithm has potential applications in evaluating muscle fatigue and physical stress in various occupational settings.



(A) (B)

Figure 3. (A) Silhouette scores of the k-means clustering for different window sizes of EMG Signals, (B) scatter plot of the EMG data for two of the representative features

In addition, the k-means clustering results were integrated with the acquired location data to generate a health map of the work environment that visualizes high physical stress levels during the material handling task. The health map revealed two areas where subjects experienced high physical stress. The first high-stress area was where subjects frequently lifted heavy bags, and the second one was where they were asked to place the bags. The health map also provided a visual representation of the distribution of high physical stress across the work environment, exposing areas of the workplace that may require further improvement. The results suggest that the proposed approach can effectively identify high physical stress areas on the jobsite that can be used to inform targeted interventions to reduce worker injuries and improve workplace safety.

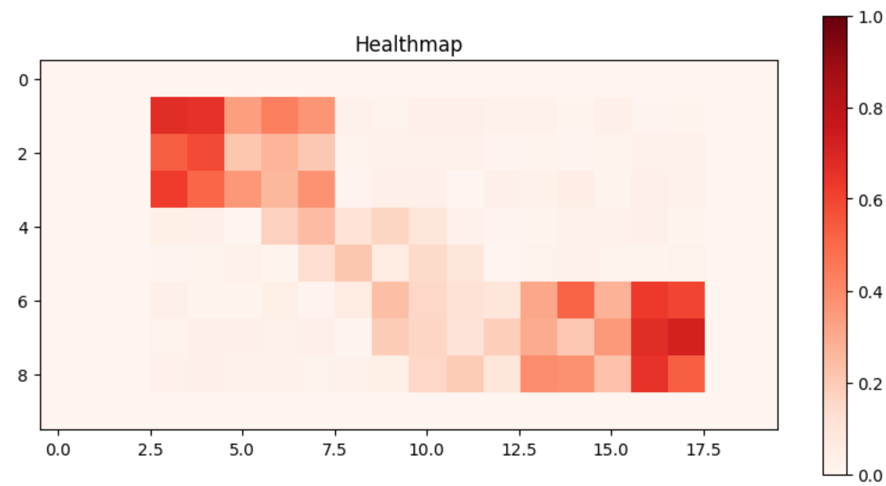


Figure 4. Generated health map of an indoor construction environment for identifying the high physical stress location and distribution.

CONCLUSION

This study explored the feasibility of using DT-based health maps for monitoring the health status of construction workers. The results demonstrate the potential of employing wearable biosensors and DT technology to capture, analyze, and visualize construction workers' physical stress in near-real-time. This novel integration can provide a comprehensive view of workers' health status for the managers and help identify potential health risks early, enabling preventive measures to reduce the incidence of work-related injuries and illnesses at construction jobsites. Besides, integrating DT technology with indoor mapping can facilitate the visualization of stress hotspots throughout the construction work environments, providing decision-makers with a better understanding of the logistics of the jobsites. As such, this study contributes to the field by demonstrating the feasibility and potential benefits of using DT-based health maps for monitoring and improving the health and safety of the construction workforce. Future research can expand on this work by incorporating more physiological metrics as well as data from other sources to develop a more comprehensive health monitoring system. In addition, investigating the usability and acceptability of the proposed DT-based system among workers and management, and addressing privacy and security concerns, are critical areas for future research.

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