Validity of facial features' geometric measurements for a real-time assessment of mental fatigue in construction equipment operators

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Abstract

Operating construction equipment for extended periods of time may lead to mental fatigue and, as a result, an increased risk of human error-related accidents and jeopardized health problems for the operators. Therefore, to limit the risk of accidents and protect operators' wellbeing, their mental fatigue must be monitored reliably and in real time. Recently, many invasive technologies have been employed to alleviate this problem, but they entail the wearing of physical sensors, which may instigate irritation and discomfort. This study proposes a non-invasive mental fatigue monitoring method using geometric measurements of their facial features that does not require the operators to wear sensors on their body. The study further validates the proposed method by comparing it with wearable electroencephalography (EEG) technology to establish its ecological validity for construction equipment operators. To serve the purpose, a one-hour excavator operation by sixteen construction equipment operators was conducted on a construction site. Ground truth, brain activity using wearable EEG, and geometric measurements of facial features were extracted and analyzed at the baseline and every 20 min for one hour. A considerable temporal variation was found in the reported metrics (eye aspect ratio, eye distance, mouth aspect ratio, face area, and head motion) and were significantly correlated with ground truth and EEG metric. Furthermore, the brain visualization pattern obtained from EEG was also associated with the variations in the facial features. The findings of the study reveal that construction equipment operators' mental fatigue can be monitored non-invasively using geometrical measurements of facial features.

Keywords: mental fatigue, construction equipment operators, construction safety, facial features, electroencephalography

1 Introduction

The construction industry has reputation for its poor safety performance (Ke et al., 2021b). Despite huge positive impacts, the safety of the workforce in the construction industry is the most neglected and unresolved challenge. Globally, the construction industry has an excessively high accident rate (ILO, 2022). More specifically, about 20% of fatal accidents in the United States and 40% of fatal accidents in Singapore happen in the construction industry (Feng et al., 2015, OSHA, 2019). Similarly, the Hong Kong construction industry also reported 2947 and 2532 accidents in 2019 and 2020, respectively. In addition, statistics for the first three months of 2022 reveal that the construction industry in Hong Kong recorded the highest number of fatalities and accident rate among all other industrial sectors (Labor, 2022). Moreover, construction has been listed as the second most accident-prone industry in Pakistan relative to other industries, and the percentage of accidents has increased significantly over the past several years. For instance, 16.27%, 17.27%, and 19.70% in 2014-15, 2017-18, and 2020-21, respectively (PBS, 2015, PBS, 2018, PBS, 2021). Besides, safety remains a key concern in the Chinese construction industry, as it accounted for over a third of all recorded incidents (CLB, 2020). Additionally, the People's Republic of China's Ministry of Emergency Management reported in 2018 that the total number of accidents had increased year-on-year and has remained high. Furthermore, the accident and death rates increased by 7.8 percent in the first half of 2018 to 1,732 accidents and 1.4 percent to 1,752 deaths, respectively (MEM, 2018). Among the overall construction accidents, equipment accounted for one fifth of the total accidents (Labor, 2016). Likewise, OSHA also found that struck-by accidents are among the four major causes of fatalities in the construction industry. Construction equipment is used in the construction industry to perform different complex tasks such as excavation, lifting materials, compaction, etc. Such tasks are mentally demanding and require the equipment operators to maintain a certain level of sustained attention and vigilance (Li et al., 2020b). Wagstaff and Sigstad Lie (2011) stated that such prolonged construction operations and vigilant tasks induce mental fatigue among construction equipment operators. When an operator is subjected to mental fatigue, he is unable to continue equipment operations due to prolonged attention. It hampers the equipment operators' judgement and concentration (Das et al., 2020). They undergo a decrease in productivity and performance (Masullo et al., 2020). This makes equipment operators more vulnerable to equipment-related accidents and, subsequently, causes workplace injuries and fatalities. Therefore, prevention of construction equipment operators' attention failure plays an important role in enhancing site safety (Han et al., 2019). Therefore, it is crucial that the mental fatigue of construction equipment operators be automatically monitored so that safety personnel can intervene immediately if necessary.

Safety is a fundamental need for anyone participating in construction work. Therefore, for construction safety, many studies have attempted to assess the mental fatigue of construction equipment operators. Initially, mental fatigue was assessed by relying on the subjective assessment of operators (Turner and Lingard, 2020). Among them, the most widely utilized subjective assessment tool is NASA-TLX (Hart, 2006). As such, this assessment was not suitable for continuous monitoring of mental fatigue since it hampers the routine work of operators, it is intrusive in nature, time-consuming, and is based on biased self-reporting of workers; hence, it lacks accuracy (Umer et al., 2020, Han et al., 2019). Over the past few decades, advances in technology have made it possible to develop devices that provide objective assessments of mental fatigue. Therefore, the researchers were motivated to perform a more objective and real-time assessment of mental fatigue using physiological measurements such as electroencephalogram (Jeon and Cai, 2022, Ke et al., 2021a, Wang et al., 2019), electrodermal activity (Umer, 2022, Lee et al., 2021, Choi et al., 2019), eye tracking (Noghabaei et al., 2021, Li et al., 2020b, Han et al., 2020) and electrocardiograph (Umer et al., 2022, Zhao et al., 2012). As a result of the fact that when a person's mental state changes, so do the values and parameters of physiological signals and their accompanying parameters (Dziuda et al., 2021). Even though these technologies have shown promising results in the diagnosis of mental fatigue, there are several issues with their use. The equipment operators must wear these devices on their bodies making them invasive in nature and at the same time causing annoyance while performing equipment operations (Li et al., 2020b). These techniques are based on the electrical conductivity of the operator's body, and electrical signals are susceptible to harsh construction site conditions. The application of these technologies sometimes requires skin preparation for sensors and also necessitates limited physical activity to minimize artifacts (Chen et al., 2015). Some of these technologies, including electroencephalography, have poor spatial resolution (Kaur et al., 2022). Due to the fact that electrodes assess surface activity, it is unknown whether the signals originate near the surface or deep within the brain region. Also, most of the studies were conducted in simulated scenarios, such as by Liu et al. (2021) and Li et al. (2019b), which limits their applicability and reliability for construction sites and equipment operators. This significantly limits their occupational use for detection of fatigue (Shi et al., 2017). Thus, there exists a knowledge gap to automatically detect the operators' mental fatigue by non-invasive and contact-free measurements without disrupting their ongoing equipment operations. Likewise, a low-cost, automated early warning system for the mental fatigue of construction equipment operators will help to make construction sites safer for operations.

Accordingly, this study proposes geometrical measurements of construction equipment operators' facial features as a manifestation of mental fatigue through non-invasive and contact-free measurements. As per the study by Ma et al. (2021), the human face not only shows direct personal information but also shows indirect emotions. Dziuda et al. (2021) reported that the continuous analysis of face images of drivers acquired while driving allows effective and contactless detection of fatigue. Similarly, Cheng et al. (2019) concluded that observing a person's facial expressions and indications can reveal clues to their level of stress and fatigue. Earlier studies also indicate the usefulness of facial features for fatigue detection. At the beginning of the 1990s, the percentage of time that the eyes were 80% to 100% closed was adopted to research fatigue in drivers (Daza et al., 2014, Zhang and Zhang, 2010). Later ranges of 70% to 100% (Lin et al., 2015) and 75% to 100% (Henni et al., 2018) of eye closure were considered in other studies. Other indicators of mental fatigue were also proposed. The most measurable indicator related to eyes were eye aspect ratio (Kuwahara et al., 2022, El Kerdawy et al., 2020), blinking rate (Bachurina and Arsalidou, 2022, Zargari Marandi et al., 2018); and eye distance (Giannakakis et al., 2017). Similarly, Wang et al. (2018) reported that as much as 80% of the information our brains get originates from our eyes. Eye behavior can therefore be utilized to evaluate our mental state. Additionally, Chew et al. (2021) analyzed gaze behavior patterns to assess the perceived workload. Nevertheless, eye blinks are also considered in the latest literature on driver fatigue research (Aravind et al., 2019). Similarly, Li et al. (2021) used self-report, eye blinking rate, and R-value as indicators to substantiate the driver's fatigue state. Additional information regarding the mental fatigue can also be obtained by tracking the position of the driver's head. It has been reported that under stressful conditions, head motions are more frequent and quicker, with a greater overall amount of head motion (Ansari et al., 2022, Giannakakis et al., 2018). Furthermore, research shows that fatigued situations have been demonstrated to have an impact on mouth-related features such as lip movement (Iwasaki and Noguchi, 2016). Similarly, Giannakakis et al. (2017) reported increased mouth activity during stressful situations.

Despite the potential of automated facial features for the mental fatigue assessment of construction equipment operators, there is a scarcity of research using geometric measurements of facial features to understand equipment operators' mental fatigue on real construction sites. Additionally, it is challenging to use findings from other occupations, such as drivers, for fatigue monitoring in excavator operators due to the substantial differences between the work patterns of drivers and excavator operators. For example, during equipment operations, excavator operators move their heads continuously to track the excavator's bucket (Liu et al., 2021). Therefore, it remains unknown whether geometric measurements of facial traits under such circumstances can still be used to detect construction equipment operators' mental fatigue. Thus, the ecological validity of the geometric measures of facial features for mental fatigue monitoring of construction operators is still questionable. Consequently, a research gap exists for the development and testing of an objective, automatic, and non-invasive method for assessing operators' mental fatigue. To fill this gap, firstly, the study proposes a non-invasive assessment of temporal geometric measurements of facial features to detect mental fatigue. Secondly, the study compares geometric measurements to wearable electroencephalography measurements, which is an established invasive method for mental fatigue assessment of construction workers. Many researchers have utilized it extensively to monitor the mental fatigue and stress of construction workers, for instance studies by Lee and Lee (2022), Wang et al. (2022), Jeon and Cai (2022), Ke et al. (2021a), Xing et al. (2020b), Li et al. (2019a), Wang et al. (2019), Jebelli et al. (2019), Jebelli et al. (2018a), Hwang et al. (2018), and Wang et al. (2017). This comparison serves to ecologically validate the geometric measurement of facial features in terms of their applicability to construction equipment operators' as well as their effective use during routine operations by operators without interfering with their on-site operations. As a result, the proposed study is expected to improve the current assessment of mental fatigue in a non-invasive way through contact-free measurements.

2 Methodology

The overview of the research process and experiment procedure is depicted in Figure 1 and Figure 2, respectively. It shows the proposed approach for identifying mental fatigue in construction equipment operators by using geometric measurements of facial features collected through video recordings. An excavator operating experiment was conducted at a construction site to collect related data for detecting the mental fatigue of construction equipment operators. On different days, the experiment was conducted at the same time, i.e., from 9:00am to 11:00am (Li et al., 2019b, Zhao et al., 2012) in the morning under similar weather conditions, i.e., clear weather on all data collection days. The experiment was based on a monotonous and prolonged excavating and discharge task on a construction site. All the excavator operators were directed to complete a monotonous and prolonged excavation task for an hour, which included ground excavation and moving the material from pits to transport vehicles. Mental fatigue was induced using the time-on-task procedure. Simultaneously with their tasks, the operators were video recorded to collect data on their facial features via a mobile camera. Besides, the NASA-TLX score was utilized to quantify the subjective assessment of equipment operators' mental workload. The subjective mental fatigue levels were assessed at the start as a baseline measurement and every 20 min for the one-hour experiment (i.e., at 20, 40, and 60 min). Geometric measurements of facial features were then extracted from each frame, and artifacts were removed using a normalization coefficient Q. It is a Euclidean distance along the nose line. Apart from visual cues, EEG data for each equipment operator was also collected for every experiment phase. For the purpose of statistical analysis, since the subjective mental fatigue levels were assessed at baseline and every 20-min experiment phase, the continuous real-time data of facial features from video frames and EEG sensor data was averaged for the respective time points (i.e., at 20, 40, and 60 min), as shown in block-B of Figure 1. Mental fatigue was detected by evaluating temporal changes in facial features and through EEG sensors between the time points. Finally, the detected mental fatigue with EEG and geometric measurements of facial features were correlated to develop ecological validity for construction equipment operators.

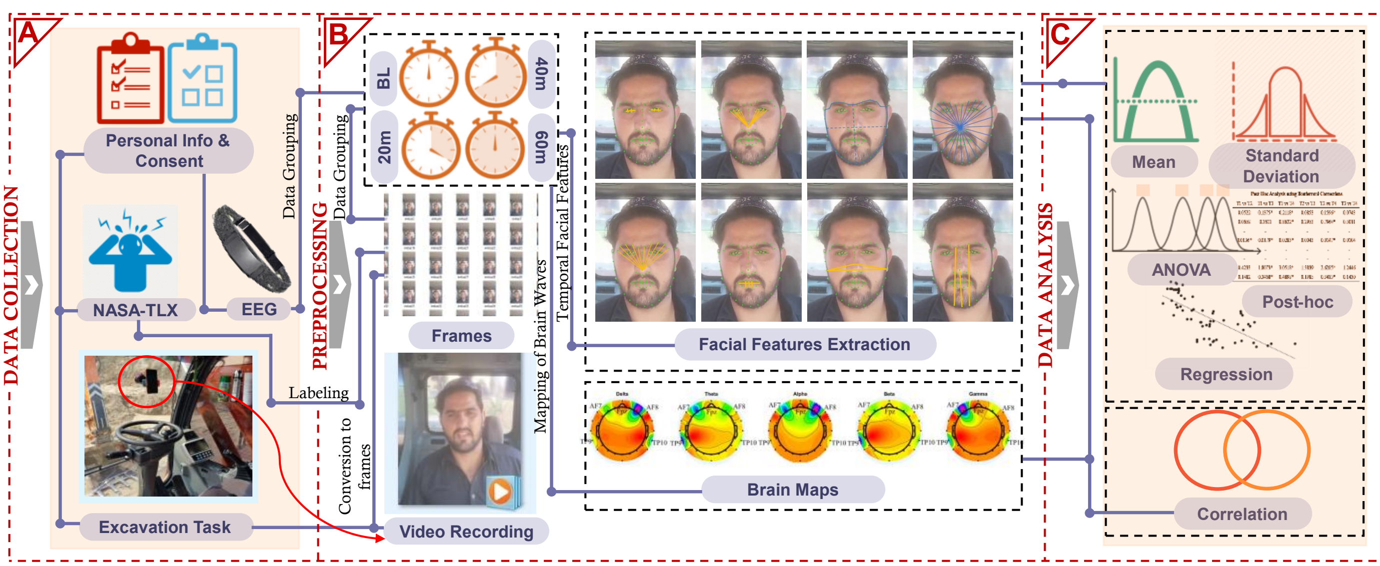

Figure 1: Overview of the research process

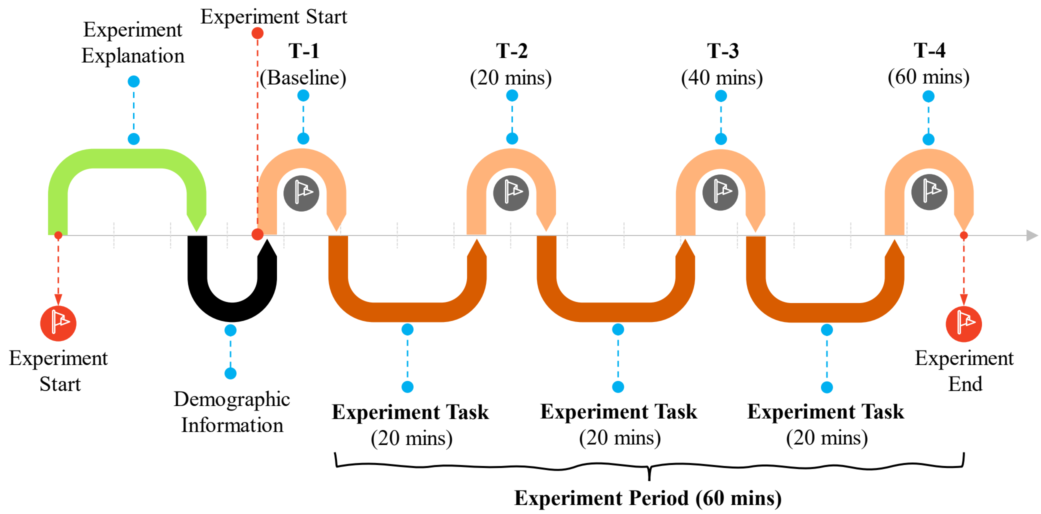

Figure 2: Experiment procedure; T1, T2, T3 and T4 represents the phases for assessments through NASA-TLX, facial features and EEG

2.1 Participants

Sixteen construction equipment operators with a mean age of 32.63 years (SD = 4.11) were included in the on-field data collection. We determined the sample size of excavator operators to recruit for our research investigations based on sample sizes from previous studies. In earlier studies with similar purposes, 12 excavator operators (Li et al., 2019b), 12 crane operators (Das et al., 2020), 11 drivers (Ahn et al., 2016), 6 excavator operators (Li et al., 2020b), and 5 crane operators (Liu et al., 2021) were recruited. Considering previous research in the literature, we decided that more than fifteen operators would be sufficient for our investigation and to justify our results. In addition, the results showed statistically significant differences, demonstrating that the sample size was adequate to infer valid conclusions. Furthermore, all the excavator operators who participated in the study were male. All the equipment operators were excavator operators, with prior experience of excavation operations at construction sites. The excavator operators indicated in their self-report that they were well rested and in good health. All the excavator operators reported having slept at least eight hours during the previous night and abstained from alcoholic drinks for 24 hours before experimentation. On their assigned day, the operators were to report directly to the experiments and perform no other duties or activities prior to the commencement of the experiment. The recruited excavation operators had normal vision and provided informed consent before the data collection. The study was approved by the ethics subcommittee of the Hong Kong Polytechnic University (Reference Number: HSEARS20210927008) and conducted in accordance with the Declaration of Helsinki. Table 1 provides the demographic information of the excavation operators.

Table 1: Construction equipment operators' demographic information

	Mean	SD	Range (Min-Max)
Age (Years)	32.63	4.11	13 (26-39)
Job Experience (Years)	7.44	2.90	9 (2-11)
Height (cm)	174.50	5.06	18 (166-184)
Weight (kg)	77.31	5.99	23 (68-91)
Body Mass Index (kg/m²)	25.43	2.29	8.30 (21.46-29.76)

2.2 Equipment and Measurement

2.2.1 Subjective assessment scales

The NASA-TLX score was used for the labeling of construction equipment operators by assessing their individual subjective feelings of mental fatigue. The NASA-TLX score was utilized to quantify equipment operators' mental workload. It has been widely used in various research investigations since its development, and its reliability and sensitivity have been tested in a consistent number of independent tests (Hart, 2006). Likewise, studies by Liu et al. (2016) and Puspawardhani et al. (2016) also stated that NASA-TLX is a popular component of research studies since it is reliable and easy to use. Furthermore, temporal increase in NASA-TLX scores for the same task is considered as a subjective indicator of mental fatigue (Li et al., 2020b). The subjective assessment was used as a ground truth for construction equipment operators' mental fatigue levels and was used to compare temporal outcomes of facial features' geometric measurements.

2.2.2 Camera-based video recording

A color video camera was mounted on the inner side of the excavator to film the operators while they sat in the cabin. The approximate distance between the operator and the camera was 0.6m. The camera was installed on the windscreen of the equipment in such a manner that the operator's usual work was not disrupted by its presence. The sampling frequency of the color video camera was 30 frames per second (24-bit RGB with three channels or 8-bit RGB per channel), with a resolution of 1440 x 1440 pixels. Furthermore, unlike other industries where the working conditions are stable, construction is a dynamic and complex industry with distinct working circumstances (Xing et al., 2020a). In this case, variations in illumination or non-uniform lighting conditions can impair facial detection performance. As discussed in the manuscript, the performance of our method depends heavily on the accurate localization of facial landmarks, which are hard to detect in low-light environments. Furthermore, we collected data from the real construction site at the same time on separate days while keeping weather forecasts in mind to avoid the extreme impacts of illumination. As a result, the overall effect of illumination and temperature was comparable for all operators. Furthermore, on days during data collection, the average minimum and maximum temperatures were 29.1°C and 30.4°C, respectively. Additionally, on all days, the weather was clear.

2.2.3 Electroencephalogram (EEG) Recording

We used the Muse headband, which is a flexible and easy-to-use EEG recording system, to acquire EEG signals.

It is a headband with four channels and dry electrodes at AF7, AF8, TP9, and TP10. FPz, being the reference electrode, is placed at the forehead position. The material used for the electrodes is silver. The Muse headband records EEG data at a sampling rate of 256 Hz. The Muse headband was linked to a smart phone through Bluetooth so that data could be transmitted. Using an app called "Mind Monitor," EEG data was recorded on a smart phone and then sent to a PC to be processed later (Arsalan et al., 2019).

2.3 Data Preprocessing

2.3.1 Data Labeling and Facial Feature Extraction

All the operators were video recorded for one hour while performing excavation operations at the construction site. Initially, each operator's captured video was transformed into frames using OpenCV (an open-source computer vision library in Python). This resulted in 108,000 frames for each operator during the whole experiment since the frequency of the camera was 30 frames per second. Subsequently, these frames for each operator were divided into four groups as per the experiment phases, i.e., baseline, 20, 40, and 60 min for further analysis. The frames were then denoted as $F_{o,p}$ where o is the excavation operator, p represents each experiment phase and expressed as vector, $p \in \{ET_1, ET_2, ET_3, ET_4\}$, 1 for baseline, 2 for data at 20 min, 3 for data at 40 min and 4 for data at 60 min. Hence, the pre-processing resulted in 16 segments of frames for each experiment phase, owing to the number of operators being 16 and each operator’s data being divided into four groups. Thus, the total number of frames processed was 1,728,000. Following the successful division of frames into experiment phases, the next stage was to recognize the faces in each frame and extract the respective facial features for further analysis. The facial detection process was performed on each frame from the video recording using a local constrained neural field model (Baltrušaitis et al., 2016). This model was applied to detect the operators' face in each frame and produced a vector L of 68 landmarks identified on the operators' face in every frame using Dlib (King, 2009) and expressed as a vector $L = [q_1, q_2, q_3, \dots \dots \dots, q_i]^T$. Where q_i is a detected face landmark in any frame with coordinates (a_i, b_i), T is the number of any frame, and i is index of detected landmarks in any frame, i.e., between 1 to 68. Eq. 1 was then used to compute the Euclidean distance between any two landmarks. This Euclidean distance was eventually used to determine the geometric measurement of eight facial features, as in the previous studies conducted by Cech and Soukupova (2016) and Bevilacqua et al. (2018). The proposed eight facial features were computed separately from each individual frame, and the details of the eight facial features have been listed in Table 2 and shown in Figure 3.

Table 2: Details of extracted facial features

Feature	**Equation**
Eye Aspect Ratio (EAR): Ratio of height and width of an eye	$EAR = \frac{\lVert p_{42} - p_{38} \rVert + \lVert p_{41} - p_{39} \rVert}{2\lVert p_{40} - p_{37} \rVert}$
Eye Distance (ED): Sum of the distance between anchor and eye landmarks.	$ED = \lVert p_{37} - p_{31} \rVert + \lVert p_{38} - p_{31} \rVert + \lVert p_{39} - p_{31} \rVert + \lVert p_{40} - p_{31} \rVert + \lVert p_{41} - p_{31} \rVert + \lVert p_{42} - p_{31} \rVert$
Eyebrow Distance (EBD): Sum of the distance between anchor and eyebrow landmarks.	$EBD = \lVert p_{23} - p_{31} \rVert + \lVert p_{24} - p_{31} \rVert + \lVert p_{25} - p_{31} \rVert + \lVert p_{26} - p_{31} \rVert + \lVert p_{27} - p_{31} \rVert$
Mouth Aspect Ratio (MAR): Ratio of height and width of mouth	$MAR = \frac{\lVert p_{68} - p_{62} \rVert + \lVert p_{67} - p_{63} \rVert + \lVert p_{66} - p_{64} \rVert}{3\lVert p_{55} - p_{49} \rVert}$
Nose to Jaw Ratio (NJR): Distance between anchor landmark and jaws	$NJR = \frac{\lVert p_{31} - p_{3} \rVert}{\lVert p_{15} - p_{3} \rVert}$
Nose to Chin Ratio (NCR): Distance between anchor landmark and chin	$NCR = \frac{2\lVert p_{31} - p_{9} \rVert}{\lVert p_{22} - p_{8} \rVert - \lVert p_{23} - p_{10} \rVert}$

Face Area (FA): Area of a closed polygon formed by joining the external landmarks on the face	$FA = \frac{1}{Q}\sum_{i=1}^{N=27}\left(S\left(S-d(p_1,p_{31})\right)^2\left(S-d(p_2,p_{31})\right)^2\left(S-d(p_1,p_2)\right)^2\right),$ $\therefore S = \frac{d(p_1,p_{31})+d(p_2,p_{31})+d(p_1,p_2)}{2}$
Head Motion (HM): Sum of the distance between anchor to external landmarks of face, per frame	$H_{mot} = \frac{1}{Q}\sum_{i=1}^{A}\lvert p_a - p_b\rvert$

Figure 3: Extraction of facial features; (a) 68 landmarks detection, (b) eye aspect ratio, (c) eyebrows (d) face area (e) nose-to-chin ratio (f) eye distance (g) mouth aspect ratio (h) nose-to-jaw ratio (i) head motion

2.3.2 Artifacts Removal

The data collected even in the experimental setting contains artifacts, which are undesired variations in the collected data due to external sources (Sweeney et al., 2012). These artifacts need to be removed since their existence within the data may easily misinterpret it and create skewness in analysis (Jebelli et al., 2018b, Hwang et al., 2018). In the case of excavator operators, they undergo continuous excessive and extreme movements during ongoing excavation operations. These movements are due to equipment vibrations as well as the movements of operators when tracking bucket to excavate and dump the earth. Such movements cause artifacts that need to be removed from the collected data. In the case of facial recognition and facial feature extraction, the facial regions having stable values are used for artifact removal. As reported in the research by Bevilacqua et al. (2018) and Giannakakis et al. (2017), the length of the nose line formed by joining the nose landmarks expressed by vector $Q = [q_{28}, \dots \dots, q_{32}]^T$ was used to remove artifacts, shown in Figure 3(a). Firstly, the landmarks shown by the vector Q were used to calculate the Euclidean distance (expressed as Eq 1) of the nose line. After that, all the facial features were then divided by Q to get normalized facial features from each frame.

$$d(q_1, q_2) = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \qquad Eq.\ 1$$

The recorded EEG signals are subjected to artifact removal techniques to remove muscular artifacts, power line noise, and other artifacts. Before analyzing the EEG data, it was subjected to preprocessing in which all the possible artifacts (muscular, power line, head motion, and eye movement artifacts) that could contaminate the EEG signal were removed as follows. Firstly, the MUSE EEG headband has an on-board noise cancellation mechanism to filter out the noise based on the statistical properties of the data. The statistical properties used by the MUSE headband include amplitude, variance, and kurtosis. An EEG signal is considered clean if its statistical properties are below a predetermined threshold; otherwise, the signal is considered noisy and discarded. Furthermore, an SG filter was used to smooth out the EEG signals that were recorded while keeping the strength of the signals. The Savitzky-Golay (SG) filter is a good way to smooth out data because it is based on the least square polynomial approximation principle (Savitzky and Golay, 1964). Different frequency (delta (0–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12-30 and beta-30) bands were used to translate the pre-processed EEG data into different frequency bands using the MUSE on-board signal processing module. The mechanism used in this study for the noise cancellation of the EEG signal has been found quite effective in several EEG studies in the literature (Raheel et al., 2021, Raheel et al., 2020, Abd Rahman and Othman, 2016).

2.4 **Data Analysis**

The data was analyzed using SPSS version 22 (IBM Inc., Chicago, IL) and statistical analysis was performed based on eight facial features for mental fatigue detection, including eye aspect ratio (EAR), eye distance (ED), eyebrow distance (EBD), mouth aspect ratio (MAR), Nose to Jaw ratio (NJR), Nose to Chin ratio (NCR), Face Area (FA), Head Motion (HM), NASA-TLX score, and EEG signals. Twenty-seven thousand frames were extracted from each equipment operator's face during each experiment phase, and one value of each facial feature was calculated from each frame, culminating in a dataset of twenty-seven thousand facial features for each equipment operator during any experiment phase. After that, for descriptive representation, standard deviation (SD) and mean (M) values of facial features for each phase of the experiment were computed. To analyze the variations in facial features due to mental fatigue, we used general linear models for repeated measures. Four geometric measurements of each facial feature were added as within-subjects factors: at baseline (T1), at 20 min (T2), at 40 min (T3), and at 60 min (T4). Using partial eta-squared (η^2), we calculated the amount of the effect on the mean values of each characteristic and the ground truth. Within-subject repeated measures analysis of variances (ANOVAs) was used for data analysis. Consequently, the F distributions with degree of freedom was reported in the results. Furthermore, Benjamini-Hochberg was also applied for multi-comparison corrections (Izmirlian, 2020) with a 5% false discovery rate (FDR) or $q = 0.05$. Benjamini-Hochberg procedure is the most widely used statistical tool that increases the statistical power and decreases the false discovery rate (Palejev and Savov, 2021). Pearson correlational coefficients were used to assess the associations between the mean changes in geometric measurements of facial features throughout the course of the experiment and the NASA-TLX scores to validate the proposed method. Furthermore, to develop ecological validity for construction equipment operators, pearson correlation coefficients were computed between mean values of geometric measurements of facial features and EEG metric [$(\theta + \alpha) / (\alpha + \beta)$]. Because Tyas et al. (2020) reported that such an EEG metric is the most used for computation of mental fatigue.

3 Results

In the study, all 16 construction equipment operators successfully completed the experiment. Therefore, data from all operators was used for analysis.

3.1 Analysis of ground truth data

The NASA-TLX score was used as a ground truth for mental fatigue detection. Statistical analysis and descriptive statistics of the ground truth assessment are shown in Table 3. The NASA-TLX demonstrated a substantial rise in subjective mental fatigue, from 11.25 (SD = 2.77) at baseline (T-1) to 65.25 (SD = 4.85) at the end of the last experiment phase (T-4). Table 3 shows that as the experiment progressed, operators reported increasing levels of mental fatigue.

3.2 Mental fatigue related facial metrics

3.2.1 Eye aspect ratio and eye distance:

The descriptive statistics and statistical analysis of eye aspect ratio and eye distance-related facial features are provided in Table 3 and Figure 4(a) and 4(b). The recorded results revealed a decrease in eye aspect ratio from experiment phase T-1 (ratio = 0.517), T-2 (ratio = 0.465), T-3 (ratio = 0.380) to T4 (ratio = 0.306), whereas an increase in eye distance feature was found from experiment phase T-1 (2.251 pixels), T-2 (2.317 pixels), T-3 (2.613 pixels) to T-4 (3.114 pixels). In general, the construction equipment operators showed a significantly decreasing eye aspect ratio due to mental fatigue (GLM: $F(3, 45) = 25.597$, $p < 0.05$, partial $\eta_p^2 = 0.631$). Furthermore, significant differences in pairwise comparisons was found for eye aspect ratio, between the experiment phases i.e., T1-T2 ($t_{Stat} = 4.040$, $p = 0.001$), T2-T3 ($t_{Stat} = 2.785$, $p = 0.014$), T3-T4 ($t_{Stat} = 2.917$, $p = 0.011$), T1-T3 ($t_{Stat} = 3.821$, $p = 0.002$), T1-T4 ($t_{Stat} = 8.007$, $p < 0.001$), and T2-T3 ($t_{Stat} = 8.611$, $p < 0.001$) using Benjamini-Hochberg corrections, shown in Table 4. Nevertheless, the pattern was increasing ($F(3, 45) = 12.919$, $p < 0.05$, partial $\eta_p^2 = 0.463$) for eye distance feature, Likewise, using Benjamini-Hochberg multi-comparison corrections, significant differences for ED were also found in pairwise comparisons between the experiment phases, i.e., T1-T4 ($t_{Stat} = -11.635$, $p < 0.001$), and T2-T4 ($t_{Stat} = -8.247$, $p < 0.001$), shown in Table 4. However, through paired comparisons in the rest of the experiment phases for eye distance, it was discovered that the differences were not significant. The boxplots of the data statistics for both eye aspect ratio and eye distance are shown in Figures 5(a) and 5(b), respectively. Attributable to low R^2 values, the variations in these features are due to the mental fatigue of operators, as reflected by the regression analysis displayed in Figure 6 of these two facial traits with other features.

3.2.2 Eyebrows

Table 3 and Figure 4(c) provide the descriptive statistics and statistical analysis of eyebrow-related facial features. This feature is a sum of the Euclidean distance between the anchor landmark on the nose and the corresponding landmarks on the eyebrows. The results indicate that the average value of the eyebrow feature increased from experiment phase T-1 (5.976 pixels), T-2 (6.071 pixels), T-3 (6.276 pixels) to T4 (6.448 pixels). There were also significant main effects of time-on-task on eyebrow features (GLM: $F(3, 45) = 17.636$, $p < 0.05$, partial $\eta_p^2 = 0.540$). Besides, the pairwise comparisons of eyebrow features with Benjamini-Hochberg showed significant differences for Eyebrow between the experiment phases, i.e., T1-T2 ($t_{Stat} = -4.268$, $p = 0.001$), T1-T3 ($t_{Stat} = -4.463$, $p < 0.001$), T1-T4 ($t_{Stat} = -5.771$, $p < 0.001$), T2-T3 ($t_{Stat} = -3.105$, $p = 0.007$), and T2-T4 ($t_{Stat} = -5.184$, $p < 0.001$), shown in Table 4. However, the corrections for the rest of the comparisons were not significant. Besides, Figure 4(c) indicates that the average Euclidean distance for eyebrow characteristics rose from experiment phase T-1 at baseline to experiment phase T-4. Figure 5(c) depicts the boxplots of the data statistics for the eyebrow feature for all experiment phases.

3.2.3 Mouth Aspect Ratio

Table 3 and Figure 4(f) provide the descriptive statistics and statistical analysis of mouth aspect ratio related facial features. The results indicate that there was an increase in mouth aspect ratio from experiment phase T-1 (ratio = 0.301), T-2 (ratio = 0.314), T-3 (ratio = 0.318) to T4 (ratio = 0.329). Considerable main effects of time on task were also found on mouth aspect ratio (GLM: $F(3, 45) = 31.390$, $p < 0.05$, partial $\eta_p^2 = 0.677$). Subsequent pairwise comparisons with Benjamini-Hochberg corrections showed notable differences in mouth aspect ratio for each of the experiment phases i.e., T1-T2 ($t_{Stat} = -6.584$, $p < 0.001$), T1-T3 ($t_{Stat} = -9.511$, $p < 0.001$), T1-T4 ($t_{Stat} = -7.026$, $p < 0.001$), T2-T3 ($t_{Stat} = -2.516$, $p = 0.024$), T2-T4 ($t_{Stat} = -4.524$, $p < 0.001$), and T3-T4 ($t_{Stat} = -2.686$, $p = 0.017$), shown in Table 4. However, the rest of the pairwise comparisons were not statistically significant. The pairwise comparison also indicated that the mean value of the mouth aspect ratio at baseline was significantly shorter than at rest of the experiment phases. As shown in Figure 4(f), all other pairwise comparisons were not statistically significant. Moreover, Figure 5(d) depicts boxplots of the mouth aspect ratio data statistics for each experiment phase. Attributable to low R^2 values, it can be concluded that the variation in mouth aspect ratio is due to the mental fatigue of operators, as depicted by the regression analysis displayed in Figure 6 of this trait with other features.

3.2.4 Nose to Jaw Ratio and Nose to Chin Ratio

Table 3, Figures 4(d) and 4(e) provide the descriptive statistics and statistical analysis of nose-to-jaw ratio and nose-to-chin ratio related facial features. The results indicate that the variation in nose-to-jaw ratio was not monotonous during the experiment phases; T-1 (ratio = 3.272), T-2 (ratio = 3.235), T-3 (ratio = 3.249) to T4 (ratio = 3.163), whereas a decrease pattern was found in the mean value of nose-to-chin ratio during the experiment phases; T-1 (ratio = 2.119), T-2 (ratio = 2.058), T-3 (ratio = 1.897) to T-4 (ratio = 1.841). Considerable main effects of time on task on the nose-to-jaw ratio (GLM: $F(3, 45) = 1.067$, $p > 0.05$, partial $\eta_p^2 = 0.066$) was not found. Nevertheless, the construction equipment operators showed a significantly decreasing nose to chin ratio due to mental fatigue (GLM: $F(3, 45) = 12.627$, $p < 0.05$, partial $\eta_p^2 = 0.457$) with significant differences in pairwise comparisons was found using Benjamini-Hochberg corrections, between the experiment settings i.e., T1-T2 ($t_{Stat} = 3.037$, $p = 0.008$), T1-T3 ($t_{Stat} = 4.836$, $p < 0.001$), T1-T4 ($t_{Stat} = 4.041$, $p = 0.001$), and T2-T3 ($t_{Stat} = 3.949$, $p = 0.001$), T2-T4 ($t_{Stat} = 3.431$, $p = 0.004$), shown in Table 4. However, the pairwise comparisons for NTC were not statistically significant between the last two experiment phases, i.e., T3 and T4. Furthermore, Figures 5(e) and 5(f) show boxplots of data statistics for nose to chin ratio and nose to jaw ratio across all experiment phases.

3.2.5 Face Area and Head Motion

Table 3, Figures 4(g) and 4(h) provides the descriptive statistics and statistical analysis of face area and head motion related facial features. The results indicate that there was an increase in the mean values of face area (FA) feature from experiment phase T-1 (8.653 pixels^2), T-2 (9.077 pixels^2), T-3 (10.461 pixels^2) to T4 (11.705 pixels^2). Besides, an increase in the mean value of head motion (HM) feature was also recorded from experiment phase T-1 (5.659 pixels/frame), T-2 (5.807 pixels/frame), T-3 (6.006 pixels/frame) to T-4 (6.149 pixels/frame). During the excavation operation, a significantly increasing pattern was found in the geometrical measurements of both the facial features i.e., face area (GLM: $F(3, 45) = 24.444$, $p < 0.05$, partial $\eta_p^2 = 0.620$) and head motion (GLM: $F(3, 45) = 32.546$, $p < 0.05$, partial $\eta_p^2 = 0.685$). Subsequently, pairwise comparisons with Benjamini-Hochberg corrections showed significant difference in the mean values of FA for all the experiment settings i.e., T1-T2 (t_{Stat} = -5.238, p < 0.001), T1-T3 (t_{Stat} = -5.192, p < 0.001), T1-T4 (t_{Stat} = -7.215, p < 0.001), T2-T3 (t_{Stat} = -3.911, p = 0.001), T2-T4 (t_{Stat} = -5.924, p < 0.001), and T3-T4 (t_{Stat} = -2.208, p = 0.043), shown in Table 4. Similarly, using Benjamini-Hochberg multi-comparison corrections, significant differences in pairwise comparisons were found for head motions between the experiment phases, i.e., T1-T2 (t_{Stat} = -6.657, p < 0.001), T1-T3 (t_{Stat} = -6.635, p < 0.001), T1-T4 (t_{Stat} = -9.328, p < 0.001), T2-T3 (t_{Stat} = -4.423, and p < 0.001), and T2-T4 (t_{Stat} = -5.684, p < 0.001). However, the rest of pairwise comparisons for both the facial features were not significant. The boxplots of the data statistics for face area and head motion during all phases of the experiment are shown in Figures 5(g) and 5(h). Due to low R2 values, it can be concluded that the changes in these traits are due to mental fatigue of operators, as demonstrated by the regression analysis showed in Figure 6.

Table 3: Means and standard deviations of mental fatigue metrics in different time phases

Metrics	**Time**			
	Baseline (T1)	**20 mins (T2)**	**40 mins (T3)**	**60 mins (T4)**
Subjective Assessment				
NASA-TLX Score (0-100)	11.25 (2.77)	30.81 (2.99)	45.00 (4.27)	65.25 (4.85)
Facial Features				
Eye Aspect Ratio	0.517 (0.116)	0.465 (0.086)	0.380 (0.103)	0.306 (0.024)
Eye Distance (pixels)	2.251 (0.523)	2.317 (0.532)	2.613 (0.783)	3.114 (0.681)
Eyebrow (pixels)	5.976 (0.582)	6.071 (0.595)	6.276 (0.778)	6.448 (0.777)
Mouth Aspect Ratio	0.301 (0.013)	0.314 (0.014)	0.318 (0.013)	0.329 (0.016)
Nose to Jaw Ratio	3.272 (0.166)	3.235 (0.153)	3.249 (0.255)	3.163 (0.277)
Nose to Chin Ratio	2.119 (0.604)	2.058 (0.576)	1.897 (0.569)	1.841 (0.478)
Face Area (pixels^2)	8.653 (0.809)	9.077 (0.857)	10.461 (1.606)	11.705 (2.128)
Head Motion (pixels per frame)	5.659 (0.166)	5.807 (0.161)	6.006 (0.295)	6.149 (0.322)

Table 4: Significance of facial feature with respect to various timepoints

Metrics	**ANOVA**		η^2	**Multi-Comparison Corrections using Benjamini-Hochberg**					
	F	***P***		T1 vs T2	T1 vs T3	T1 vs T4	T2 vs T3	T2 vs T4	T3 vs T4
EAR	25.597	≤ 0.05	0.631	4.040*	3.821*	8.007*	2.785*	8.611*	2.917*
ED	12.919	≤ 0.05	0.463	-0.841	-2.101	-11.635*	-1.359	-8.247*	-2.348
EB	17.636	≤ 0.05	0.540	-4.268*	-4.463*	-5.771*	-3.105*	-5.184*	-1.810
MAR	31.390	≤ 0.05	0.677	-6.584*	-9.511*	-7.026*	-2.516*	-4.524*	-2.686*
NJR	1.067	≥ 0.05	0.066	-	-	-	-	-	-
NCR	12.627	≤ 0.05	0.457	3.037*	4.836*	4.041*	3.949*	3.431*	0.957
FA	24.444	≤ 0.05	0.620	-5.238	-5.192*	-7.215	-3.911*	-5.924*	-2.208*
HM	32.546	≤ 0.05	0.685	-6.657*	-6.635*	-9.328*	-4.423*	-5.684*	-1.919

*EAR is Eye Aspect Ratio; ED is Eye Distance; EB is Eyebrow; MAR is Mouth Aspect Ratio; NJR is Nose to Jaw Ratio; NCR is Nose to Chin Ratio; FA is Face Area; HM is Head Motion; η^2 is effect size Partial eta-squared; *The t_{Stat} is significant at the $p < 0.05$*

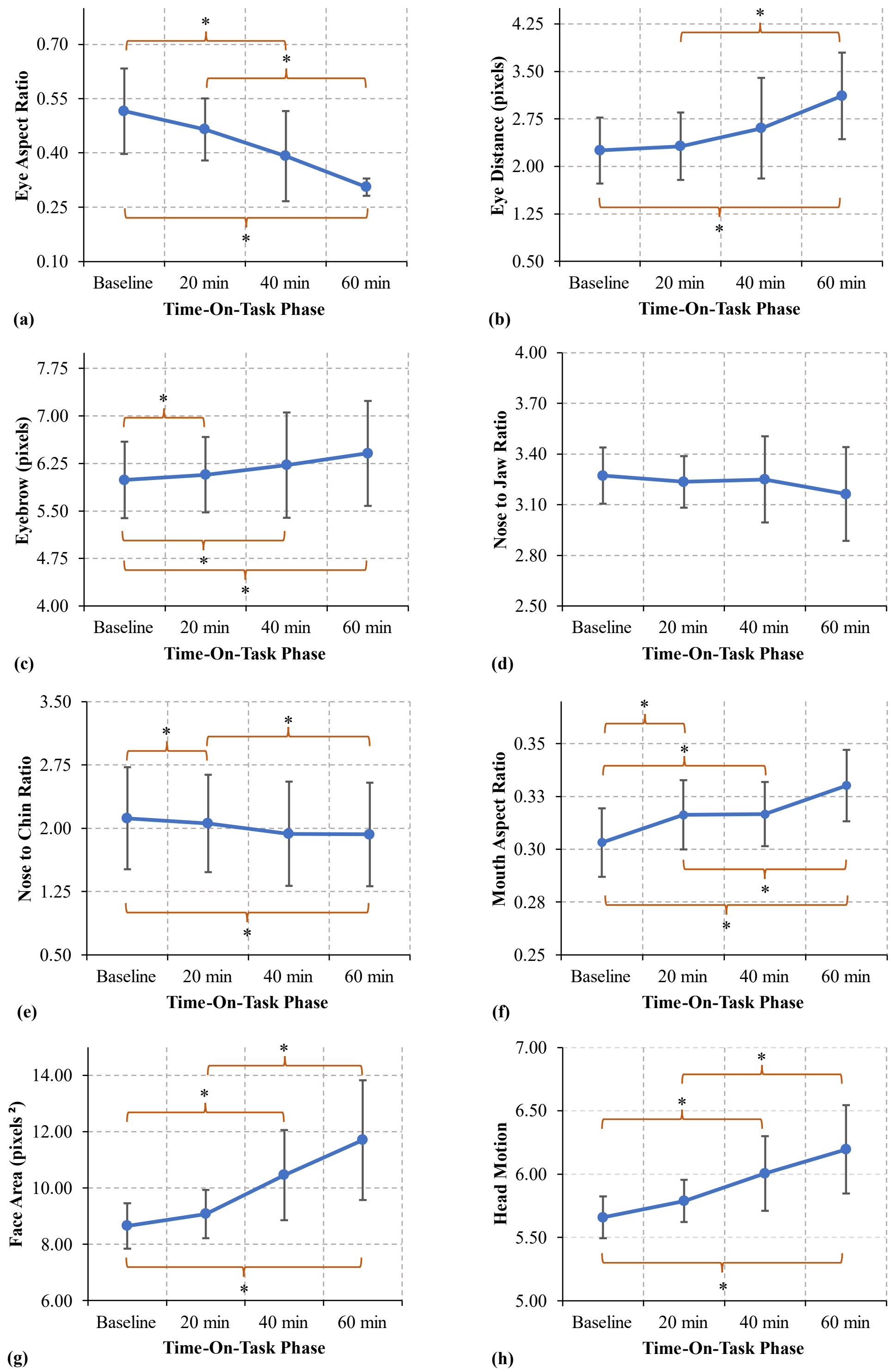

Figure 4: Variation in facial features due to mental fatigue with increasing Time-On-Task phases, (a) eye aspect ratio; (b) eye distance; (c) eyebrow; (d) nose to jaw ratio; (e) nose to chin ratio; (f) mouth aspect ratio; (g) face area; (h) head motion

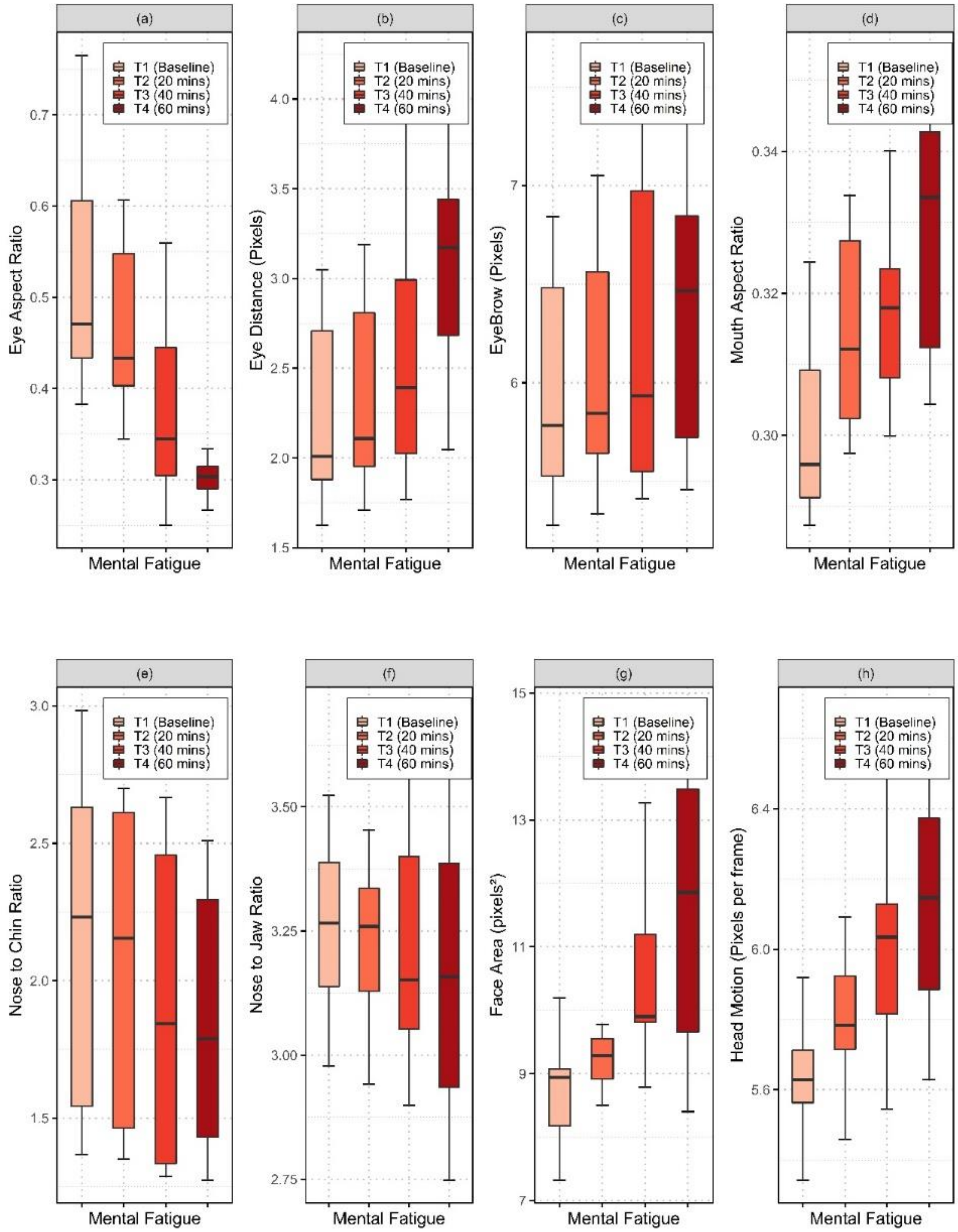

Figure 5: Boxplots for facial features (a) eye aspect ratio (b) eye distance (c) eyebrow (d) mouth aspect ratio (e) nose to chin ratio (f) nose to jaw ratio (g) face area and (h) head motion

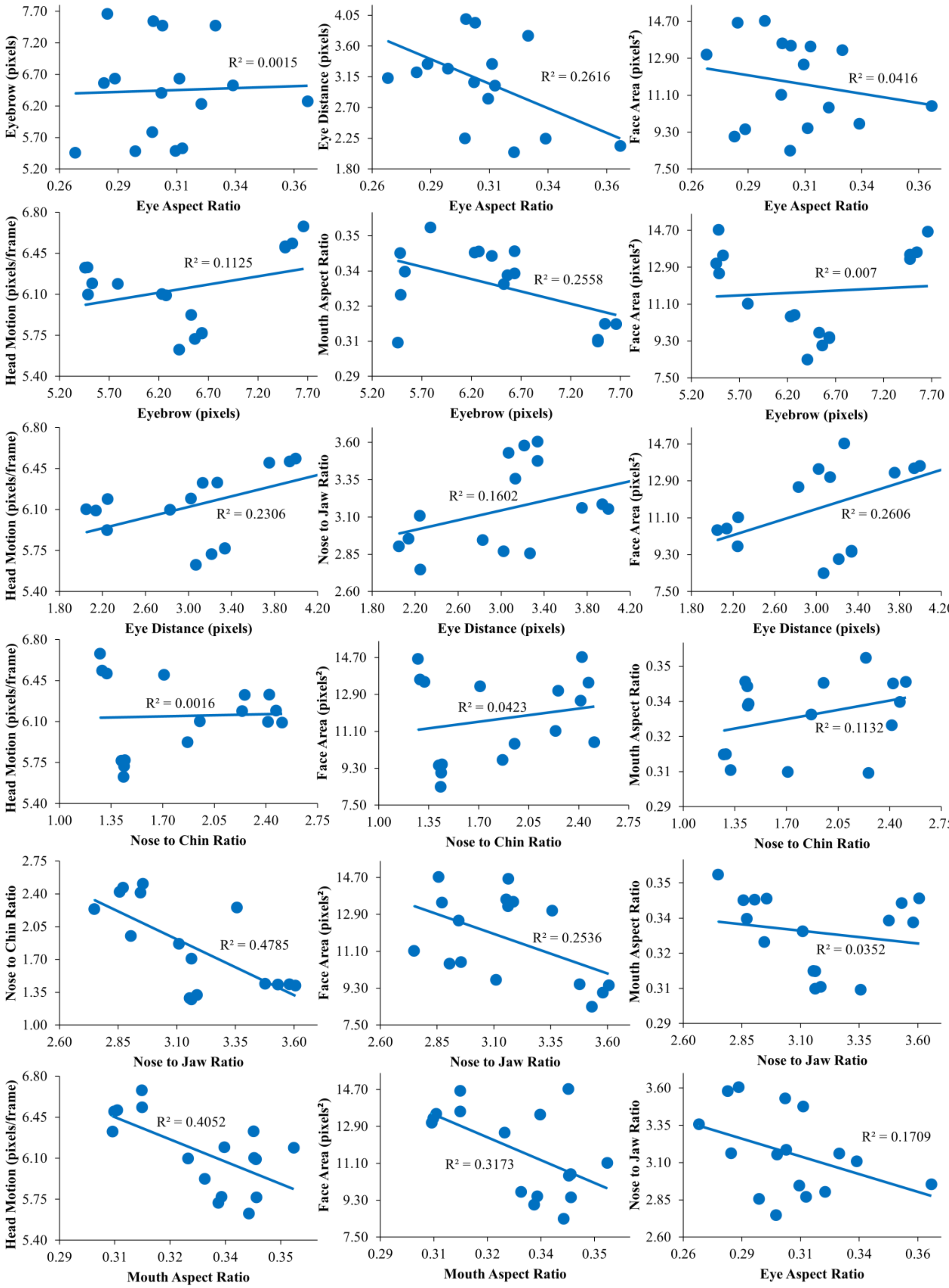

Figure 6: Regression statistics between individual facial features at the end of experiment

3.3 Analysis of physiological data

Analysis of the physiological signals EEG was performed by applying the paired t-test on the absolute power for each frequency band of the EEG signal obtained from all the channels of the MUSE headband during the four experimental phases: baseline, at 20 min, 40 min, and 60 min. A null hypothesis and p-value were used to determine the t-test decision. The difference between the groups was considered significantly different if the p-value was less than 0.05 and the null hypothesis was 1. Table 5 shows a statistically significant difference according to the results of *p*- value for EEG power spectral density in different brain regions. For example, the *t*-test applied to EEG signals revealed that the alpha band was found to be statistically significant at right frontal channel AF8 (between all experiment phases at baseline and 20 mins; 20 mins and 40 mins) and at left frontal channel AF7, it was statistically significant between experiment phases 20 mins and 40 mins only. Likewise, the beta band was found to be statistically significant at left frontal channel AF7 (between experiment phases at 40 mins and 60 mins only) and frontal channel AF8 between all experiment phases. The Delta and gamma bands were found to be statistically significant in the left and right temporal regions. The beta band, on the other hand, showed differences that were statistically significant in both the frontal and temporal parts of the brain. The statistical analysis for all the bands in the respective channels is demonstrated in Table 5. Figure 7 shows the brain activity visualization obtained using the power spectral density of the EEG data of the construction equipment operators during the four phases of the experiment. On the brain maps, the red color shows strong cortical activity, while the orange color shows little brain activity. It can be observed from the brain maps that the alpha and beta bands of AF7 and AF8 frontal channels have visually distinct brain activity at baseline, 20 min, 40 min, and 60 min of the experiment.

Table 5: p-value for EEG power spectral densities in different brain regions

Time	Channels	EEG Frequency Bands (p values by t-test)				
		Delta	**Theta**	**Alpha**	**Beta**	**Gamma**
T1 – T2 (0 & 20 min)	AF7	7.011E-09*	0.00071*	0.06148	0.62845	0.09649
	AF8	2.924E-09*	1.438E-09*	0.04877*	1.345E-05*	2.519E-05*
	TP9	3.425E-05*	0.45987	0.56974	0.00568*	1.671E-17*
	TP10	0.00167*	2.883E-07*	1.446E-10*	1.959E-12*	7.304E-13*
T2 – T3 (20 & 40 min)	AF7	4.214E-05*	0.55471	0.00023*	0.76902	0.08094
	AF8	0.60858	0.00053*	0.00016*	3.219E-06*	0.13631
	TP9	0.02326*	0.52230	0.20485	1.716E-06*	0.18105
	TP10	0.01776*	0.98454	0.19671	0.12579	1.678E-11*
T3 – T4 (40 & 60 min)	AF7	0.13977	0.71663	0.97207	0.00155*	0.00023*
	AF8	0.00480*	0.00295*	0.00241*	0.00026*	0.00024*
	TP9	0.00882*	0.00046*	0.01284*	0.00357*	0.00627*
	TP10	0.01746*	5.106E-05*	0.17877	0.00441*	0.00289*

**The mean difference is significant at the 0.05 level*

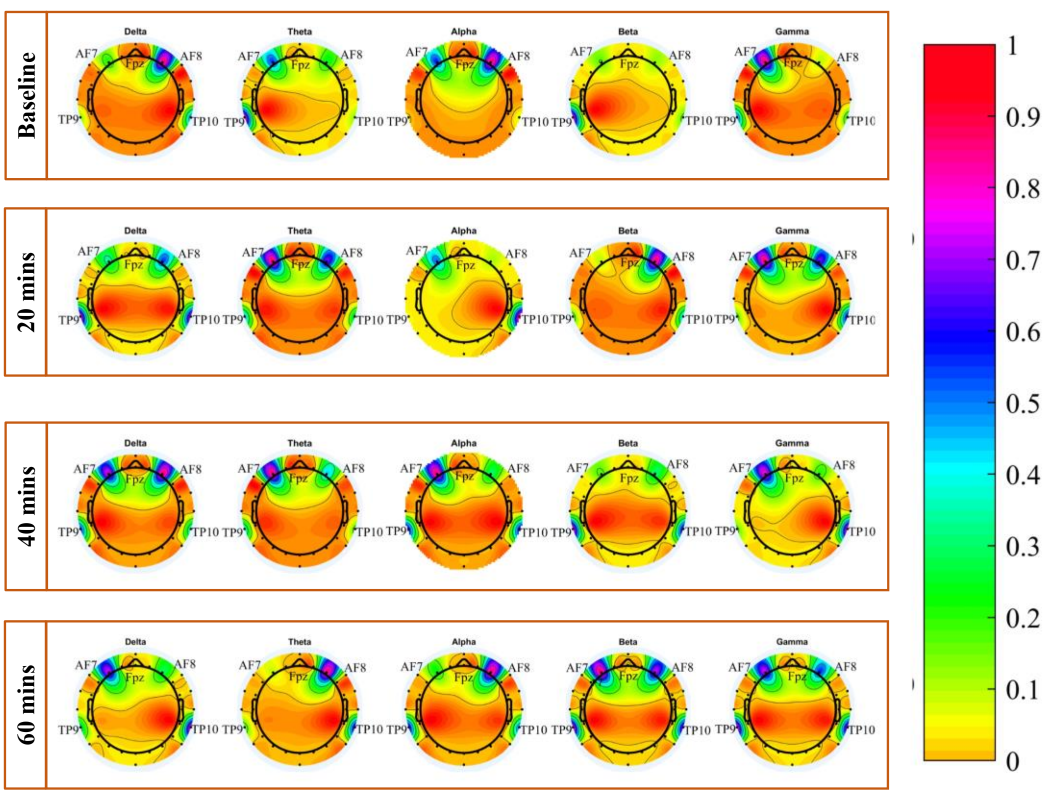

Figure 7: Brain activity visualization in terms of power spectral density of different EEG bands for the four experiment phases

3.4 Validity of the facial features' geometric measurements

3.4.1 Correlations between facial features' geometric measurements and subjective mental fatigue scores

In Table 6, correlations between geometric measurements of facial features and subjective mental fatigue scores are shown. The eye aspect ratio at T-1 (r = -0.5202), T-3 (r = -0.6730), and T-4 (r = -0.5760) minutes of the experiment was significantly correlated with the corresponding subjective mental fatigue scores. Similarly, geometric measurements of eye distance facial features were significantly associated with subjective mental fatigue scores during all the experiment phases; T-1 (r = 0.7164), T-2 (r = 0.5029), T-3 (r = 0.6866) and T-4 (r = 0.9264). Furthermore, across all experiment phases, the head motion face feature was substantially linked with the corresponding subjective scores. However, mouth aspect ratio was only correlated at T-4 (r = -0.5872). Also, at experiment phases T3 (r = 0.5884) and T-4 (r = 0.5078), face area feature was related. However, there was no association between the remaining facial features (e.g., eyebrows, nose to chin ratio, and nose to jaw ratio) and subjective mental fatigue.

Table 6: Correlations between facial features and subjective scores of mental fatigues

Parameters	**NASA-TLX Score**				
	Time	**Baseline**	**20 min**	**40 min**	**60 min**
Eye Aspect Ratio	Baseline	-0.5202*			
	20 min		-0.4635		
	40 min			-0.6730**	
	60 min				-0.5760*
Eye Distance (Pixels)	Baseline	0.7164**			
	20 min		0.5029*		
	40 min			0.6866**	
	60 min				0.9264**
Eyebrow (Pixels)	Baseline	0.6318**			
	20 min		0.7327**		

	40 min			0.5695*	
	60 min				0.5967*
Mouth Aspect Ratio	Baseline	0.0075			
	20 min		0.0762		
	40 min			0.2226	
	60 min				-0.5872*
Nose to Jaw Ratio	Baseline	0.1448			
	20 min		0.0241		
	40 min			0.4504	
	60 min				0.2912
Nose to Chin Ratio	Baseline	-0.6134*			
	20 min		-0.5954*		
	40 min			-0.5288*	
	60 min				-0.6011*
Face Area (Pixels^2)	Baseline	0.1313			
	20 min		0.1382		
	40 min			0.5884*	
	60 min				0.5078*
Head Motion (Pixels per frame)	Baseline	0.5209*			
	20 min		0.6910**		
	40 min			0.5003*	
	60 min				0.5413*

**Correlation is significant at 0.05; **Correlation is significant at 0.01*

3.4.2 Correlations between facial features' geometric measurements and EEG metric

The correlations between facial features and electroencephalography metric [$(\theta + \alpha) / (\alpha + \beta)$] for mental fatigue are shown in Table 7. The eye aspect ratio was significantly correlated with EEG during all the experiment phases, i.e., at baseline (r = 0.6849), 20 min (r = 0.5008), 40 min (r = 0.5510), and 60 min (r = -0.5760) of the experiment. Similarly, geometric measurements of head motion facial features during experiment phases; at baseline (r = -0.5042), 20 min (r = -0.6234), 40 min (r = -0.5374), and 60 min (r = -0.4985) were significantly associated with the EEG metric. Furthermore, at baseline, 20 minutes, and 60 minutes of the experiment, the eye distance facial feature was found to be significantly linked with the EEG metric. The findings also revealed that eye aspect ratio was positively associated, whereas the eye distance and head motion facial features were negatively corelated with the EEG metric. However, the correlation of rest of the facial features with EEG metric was not monotonous during all the experiment phases as shown in Table 7.

Table 7: Correlation between EEG metric and facial features

Facial Features	**EEG Metric [(θ + α) / (α + β)]**			
	Baseline	**20 mins**	**40 mins**	**60 mins**
Eye Aspect Ratio	0.6849*	0.5008*	0.5510*	0.6505*
Eye Distance	-0.6701*	-0.3608	-0.5497*	-0.7155*
Eyebrow	-0.5698*	-0.6034*	-0.4507	-0.2246
Nose to Jaw Ratio	-0.4007	-0.3472	-0.3618	-0.1323
Nose to Chin Ratio	0.5861*	0.4915	0.4717	0.2269
Mouth Aspect Ratio	0.1600	0.4466	0.1282	0.3830
Face Area	-0.1311	-0.3872	-0.5566*	-0.5881*
Head Motion	-0.5042*	-0.6234*	-0.5374*	-0.4985*

**Correlation is significant at the 0.05 level*

4 Discussion

The current study is the first of its kind in the construction industry because of its non-invasive methodology. According to the results of the subjective assessment and variations in geometric measurements of facial features, individuals experienced increasing mental fatigue after participating in the experiment phases. The findings are statistically significant and support the idea of monitoring mental fatigue using geometric measurements of facial features. As far as the authors know, no study has compared the proposed method to invasive methods like electroencephalography that are used to monitor mental fatigue in construction equipment operators.

4.1 Variations in the facial features' geometric measurements

The findings of this research are in line with those conducted in non-construction domains that have utilized facial features for mental fatigue detection. The current study used geometric measurements of eight facial features: eye aspect ratio, eye distance, eyebrow, nose to chin ratio, nose to jaw ratio, mouth aspect ratio, and head motion. Comparable studies in non-construction domains have used eye-related variables for mental fatigue detection with similar findings. There was a statistically significant difference in eye aspect ratio and eye distance. From baseline until the end of the experiment, they demonstrated a rise in the mean values of eye distance and a decrease in the mean values of eye aspect ratio. The variation in mean values reveals that landmarks were moved closer together as mental fatigue increased among equipment operators. Therefore, such a variation pattern is suggestive of increased blinking and eye closure due to increased mental fatigue. Hence, the construction equipment operators' cognitive effort increased. Likewise, the study found an increase in the eyebrow. However, the increase was not statistically significant. The results are aligned with the previous studies that showed an increase in the blinking of eyes during fatigue states. For example, Giannakakis et al. (2017) and Norzali et al. (2014) reported an increase in the blink rate under stressful situations and concluded that blink rate and mental stress are highly correlated with each other. Nevertheless, Wenhui et al. (2005) reported that the eye blinks decreased with an increase in cognitive effort. A change in eye metrics was also found by Bevilacqua et al. (2018) in a study where subjects were subjected to stressful scenarios of a game. Likewise, Ravaja et al. (2006) also stated an increase in orbicularis oculi (a muscle associated with eyelid movement) electromyography activity in non-neutral emotional states. Our study found no statistically significant differences in eyebrow activity among operators, although the variation is consistent with earlier research. For example, a study by Kimmelman et al. (2020) stated that eyebrow positions are affected by emotional states.

Mouth-related features of construction equipment operators appear to be indicators of mental fatigue. This study demonstrated an increase in the mean mouth aspect ratio from baseline to the last experiment phase. The increase was statistically significant. The increase in mean values indicates that the position of mouth landmarks strayed away from each other due to increased mental fatigue. Similarly, such a change may be indicative of frequent mouth movements with an increase in mental fatigue. For example, a study by Giannakakis et al. (2017) reported that an increased variation and median of the highest magnitude of mouth activity imply faster mouth movements during stressful conditions. Similarly, as studied by Tang et al. (2016), the mouth remains closed in a normal state while it opens when a subject is in fatigued state. Likewise, Tijs et al. (2008) reported that in emotional states, the zygomatic (a face muscle that is linked to the mouth) is more active.

Mental fatigue also affects facial traits linked to construction equipment operators' dynamic body motions, such as head motion, face area, nose to chin ratio, and nose to jaw ratio. Bevilacqua et al. (2018) stated these dynamic body movements as head movement and physical posture. The operator's head moves vertically, horizontally, and rotationally while operating. Thus, the increase in the mean value of this feature demonstrates that as the experiment progressed, the operators' head motion increased due to mental fatigue. Table 3 shows the change, which is statistically significant throughout all experiment stages, indicating greater mental fatigue. Similarly, the current study analyzed nose to jaw and nose to chin ratios. The preceding was to represent the face's shift to the right or left. The latter feature reflected the operator's face tilting upward or downward. The mean nose to chin ratio decreased from the baseline to the completion of the excavation experiment. It is because the operators were advancing towards the camera, but their faces were tilted upwards, indicating they were attempting to keep their focus on the task despite fatigue. However, the differences between the phases were not statistically significant. The present study's findings accord with past research in other sectors. For example, Liao et al. (2005) and Dinges et al. (2005) found an increase in head movements during non-neutral states. Furthermore, studies by Kusano et al. (2020), Giannakakis et al. (2018), and Giannakakis et al. (2017) also reported an increased head motion under stressful situations such as watching videos. Nevertheless, results from the current study are contrary to the findings by Bevilacqua et al. (2018), where no statistical significance was reported between boring and stressful states.

Additionally, the current study also studied the face area feature which was associated with the movement of equipment operators towards and away from the camera. The current study demonstrated an increase in face area, indicating the movement of operators towards the camera. The increase between the subsequent experiment phases from baseline was 4.90%, 15.24%, and 11.89%, respectively. The findings are consistent with the previous study by Bevilacqua et al. (2018) where there was an increase in the face area of subjects during a stressful state.

4.2 Relationship of facial features' geometric measurements with subjective and objective assessment

During the excavation operation experiment, there were strong relationships between geometric measurements of facial features and subjective mental fatigue scores. Some variables correlated with subjective scores throughout the entire experiment, while others only correlated at one or two stages. For example, face area features were substantially linked with subjective scores during the final two experiment phases, i.e., at 40 and 60 minutes, shown in Table 6. Previous studies have found that fatigue assessments are substantially connected to eye-related cues (Sundelin et al., 2013). Likewise, a study by Hopstaken et al. (2015) also reported an increase in subjective mental fatigue and a decrease in baseline pupil diameter as a result of increasing time spent on the activity, with a corresponding decrease in cognitive performance. Similarly, a study by Dziuda et al. (2021) also found that the drivers' responses to the fatigue symptoms scale questionnaire before and after the simulator task were found to be correlated with changes in their percentage closure of eye time levels.

This study found a difference between EEG bands (baseline, 20 min, 40 min, and 60 min) in the evolution of mental fatigue. After an hour of continuous operation of construction equipment, we found alterations in spontaneous brain activity. Five EEG patterns were evaluated in four brain areas: AF7, AF8, TP9, and TP10. Figure 4 shows the brain maps using the power spectral density of EEG data from construction equipment operators at the outset, 20 minutes, 40 minutes, and 60 minutes of the experiment. The beta band's power covers the entire brain. The temporal delta and gamma bands revealed a consistent trend. The frontal alpha band rhythm was not monotonous. Figure 4 depicts the frontal and temporal lobes of the brain becoming fatigued as the experiment progressed. In some areas, the theta band colors are redder and bluer. The p-values for statistical significance are also monotonous. The findings are consistent with previous research on fatigue (Li et al., 2020a, Eoh et al., 2005). Theta waves, which are linked to brain fatigue, appear early in the sleep cycle, making them sensitive to mental fatigue (Lal and Craig, 2005, Åkerstedt and Gillberg, 1990). Alpha rhythm indicates the condition of relaxation and wakefulness (Li et al., 2020a). In the third and fourth experiment phases of the study, alpha activity was observed in the frontal channels shown, in Figure 4, which is in line with previous research. For example, studies by Eoh et al. (2005) and Lal and Craig (2002) reported that the potency of the alpha pattern increases with an increase in mental fatigue. Similarly, another study by Sun et al. (2014) and Craig et al. (2012) also reported that with an increase in mental fatigue, the power of the alpha band increases. This is why it is considered the most reliable indication of mental fatigue (Lal and Craig, 2005). During the excavation operation experiment, there were strong relationships between geometric measurements of facial features and EEG metric. Some variables corresponded with subjective scores throughout all experiment phases, while others correlated at one or two stages only. For example, eye aspect ratio, eye distance, and head motion were substantially linked to the EEG metric during all the experiment phases. As the construction equipment operators were subjected to mental fatigue, their eye aspect ratio decreased, and their eye distance increased from the baseline. The decrease in eye aspect ratio indicates the closing of eyes, thus indicating theta band activity in the brain topography. Likewise, the increase in face area and head motion indicates that the equipment operators were trying to increase their concentration by moving close to the windscreen of the equipment and camera. However, the association of the rest of the facial features with the EEG metric was not found to be monotonous during each of the experiment phases. Overall, geometric measures of facial features produce statistical conclusions that agree with the visual representations of the brain as a result.

4.3 Implications

The proposed research study is expected to inspire changes in safety management practices on construction sites. Using geometric measurements of the construction equipment operators' facial features, this study proposed a non-invasive mental fatigue monitoring method that did not require the operators to wear sensors on their body. Apart from determining the effectiveness of the proposed method, the study also compared the results with electroencephalography (EEG), which is an invasive mental fatigue monitoring method. The findings of this research have both practical and theoretical repercussions for alleviating the mental fatigue of construction equipment operators. Firstly, the method being proposed herein, apart from detecting construction equipment operators' mental fatigue, can also be useful for real-time facial features-based monitoring of mental fatigue on construction sites. Thus, the findings of this study reveal that it is feasible to use geometric measurements of facial features for mental fatigue detection during construction operations. Secondly, for construction managers, the findings can help them develop a framework for managing shifts among workers. For one hour, the researchers in the current study monitored changes in construction equipment operators' facial features and brain activity. Equipment operators can be observed by managers every 30 or 45 minutes of construction work. Breaks between shifts can be implemented to provide equipment operators a chance to rest and recuperate from the mental fatigue they've triggered. Thirdly, the current method is non-invasive. It involves the use of a remote camera as a sensor to take measurements of facial features without making physical contact. As a result, this method represents a significant shift from earlier construction worker wearable sensor techniques such as those studied by Ke et al. (2021b), Li et al. (2020b), Choi et al. (2019) and Hwang et al. (2018). Fourthly, as stated by Li et al. (2019b), the rate of accretion of mental fatigue among equipment operators may be higher than the laboratory setting. Consequently, the data collected for the study was from real construction sites. Therefore, the results advocate the ecological validity of this method for construction equipment operators. As a result, geometric measures of facial features open up new possibilities for contactless mental fatigue management among construction equipment operators.

4.4 Limitations and future research

This study is the first of its kind to use geometric measurements of facial and EEG to monitor mental fatigue among construction equipment operators, yet this study was subject to limitations that need to be addressed in future research work. Firstly, this study studied temporal changes in the geometric measurements of facial features at baseline, 20, 40, and 60 mins to monitor mental fatigue. The results were further validated by comparing them with statistical analysis of the power spectral density of electroencephalography of construction equipment operators. However, for future studies, a machine learning approach is advised to automatically identify the geometric measurements of facial features. Furthermore, future studies are also recommended to calculate the degree of mental fatigue by addressing its identification as a regression problem. Secondly, lighting fluctuations are believed to have an impact on the geometric measurements of face feature detection (Tran et al., 2019, Lee et al., 2018). To avoid this, we ran the experiments on the construction site at the same time each day for the subsequent days under similar weather conditions. However, in future we intend to acquire to data at various times throughout the day such as morning and evening, under varying weather conditions, to see how fluctuations in lighting on construction sites affect the results connected to facial feature geometric measures and mental fatigue monitoring. Thirdly, there may be a wide range of circumstances that can influence the appearance of a construction equipment operator's facial features. It is imperative that future research explore the effects of age (Boutet et al., 2015), experience, and other factors on the ability to discern mental fatigue based on facial features during equipment operations. Lastly, this research only investigated geometric measurements of facial features and EEG in equipment operators. Since there is no publicly available dataset for construction equipment operators and because deep learning requires a lot of data, the current study does not apply deep learning techniques to automatically identify mental fatigue. So, in the future, researchers might use recurrent neural networks (RNNs) to track the mental fatigue of people who operate construction equipment by gathering a lot of data from real construction sites.

5 Conclusions

Mental fatigue led attention failure of equipment operators is associated with the collisions between construction equipment and surrounding site objects that lead to accidents causing injuries and fatalities. Therefore, the current study developed a construction site procedure to detect construction equipment operators' mental fatigue, which is a promising approach to mitigate the risk of equipment-related accidents. As a result, we performed an automated analysis of geometric measures of facial features from video clips in conjunction with an empirical evaluation of its applicability for construction equipment operators. To achieve this objective, 16 excavator operators were engaged to record facial videos and EEG sensor data while working on an excavation activity. Eight distinct facial features (eye aspect ratio, eye distance, eyebrows, mouth aspect ratio, nose to jaw ratio, nose to chin ratio, face area, and head motion) comprised of Euclidean distance and areas were calculated from sixty-eight facial landmarks. These facial features do not rely on 6 universal predefined facial expressions. Temporal values of these facial features' geometric measurements and EEG sensor data were compared at baseline, 20 min, 40 min, and 60 min. The results indicate that there was a statistically significant difference in the mean values for all the facial features (i.e., eye aspect ratio, eye distance, eye distance mouth aspect ratio, face area and head motion) between various experiment phases at baseline, 20, 40, and 60 min. However, the results were not statistically significant for the rest of the facial features. Consequently, the brain maps obtained using the power spectral density of the

EEG data recorded from construction equipment operators at the same time frames also advocate the fact that the operators' brains were experiencing mental fatigue. The study's key contribution is to demonstrate the ecological validity of contactless measures for detecting and evaluating mental fatigue for construction equipment operators by studying their association with wearable EEG sensor data. The study found a strong association between the proposed method and the electroencephalography metric. The proposed method's deployment is non-invasive and based on video records. Furthermore, it does not require wearable sensing technology for mental fatigue monitoring. Given the dynamic and complicated nature of construction site operations, it is believed that the proposed methodology is more user-friendly, practical, and more appropriate to the construction domain for mental fatigue monitoring. It will help to reduce equipment-related accidents, injuries, and errors on construction sites through proactive monitoring of the operator's mental fatigue.

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