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Understanding the Role of Inter-Individual Variability in Fatigue Monitoring of Construction Workers

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Abstract: Effective physical fatigue monitoring is crucial for ensuring the health, safety, and productivity of construction workers, given the physically demanding nature of their work and the challenging environment in which they operate. In recent years, wearable sensors have shown growing potential for physical fatigue monitoring among construction workers. However, such fatigue assessment methods exhibit a significant gap as they often overlook the impact of inter-individual variability, such as differences in height, weight, and body mass index, on physiological signals that indicate physical fatigue. Therefore, this study aimed to investigate the role of personal factors in altering physiological responses, thereby improving the reliability and accuracy of fatigue monitoring using wearable physiological sensors.

To explore the impact of these inter-individual factors, we experimentally analyzed the relationship between personal characteristics, physiological signals, and physical fatigue. Our findings reveal that although the inter-individual factors may not be directly correlated with fatigue levels, they significantly affect fatigue through their influence on physiological signals. Incorporation of these factors into a random forest predictive model significantly enhanced its predictive performance. Furthermore, integrating personal features with other variables to create new features in the physical fatigue prediction model notably improves its accuracy, highlighting the potential for developing personalized fatigue detection systems.

Key words: inter-individual variability, physical fatigue monitoring, wearable sensors, physiological signals

1. INTRODUCTION

Fatigue, characterized by feelings of exhaustion, diminished energy, or weariness[1], has been recognized as a leading factor contributing to accidents on construction sites. Construction work involves physically and mentally demanding tasks and is often performed in dangerous and challenging environments. Thus, construction workers are more vulnerable to fatigue[2]. Fatigue results in decreased alertness, impaired cognitive function, and diminished physical performance; thus, it jeopardizes individual safety and poses significant risks to overall project efficiency and quality[3, 4]. Hence, physical fatigue among construction workers needs to be effectively monitored and managed.

Traditionally, survey-questionnaire methodologies have been used to evaluate fatigue owing to their low cost and ease of use[5, 6]. Several self-assessment methods (such as Borg and NASA-TLX) have also been used within the construction industry to estimate fatigue level and workload[7, 8]. Despite their certain advantages, these methods are time-consuming, unsuitable for real-time monitoring, prone to human errors, and intrusive[9]. Thus, they are unsuitable for effective fatigue monitoring.

Recent advancements in wearable physiological sensing technology (i.e., miniaturization of sensing modules)[10], information processing, and big data analysis have enabled non-intrusive, real-time, and accurate fatigue monitoring in construction sites. Umer et al.[11] achieved high fatigue prediction accuracy by using a wearable wrist sensor to measure electrodermal activity (EDA) and heart rate variability (HRV). Similarly, Aryal et al.[12] used heart rate and temperature to monitor physical fatigue and an electroencephalogram (EEG) to monitor mental fatigue with an accuracy of up to 82%.

Individual physiological differences and responses to work demands can affect the accuracy of fatigue assessments derived from wearable sensors[12]. For instance, age, fitness level, sleep patterns, and individual susceptibility to fatigue can influence the response of physiological signals (such as heart rate and skin conductance) to workload, leading to misinterpretations in fatigue detection algorithms. Failing to consider this inter-individual variability can lead to false alarms, missed warnings, and ultimately ineffective fatigue management strategies.

Therefore, understanding the role of inter-individual variability in fatigue monitoring algorithms is crucial for developing reliable fatigue management solutions for construction workers. This study aimed to assess the impact of various inter-individual factors on physiological responses to fatigue, paving the way for more personalized fatigue detection at construction sites.

2. LITERATURE REVIEW

Fatigue refers to a decline in physical and/or mental capacity owing to physical, mental, or emotional strain, which can hinder various physical abilities, such as strength, speed, reaction time, coordination, decision-making, and balance[13]. It is often categorized into mental and physical fatigue. Mental fatigue is attributed to prolonged periods of cognitively demanding activities that lead to a temporal decline in cognitive performance[14]. Physical fatigue is often attributed to tasks that require physical effort and lead to a reduction in physical capacity[15]. In the construction industry, specifically construction sites, a significant portion of work involves repetitive tasks and constant exertion[2]. Construction work often involves lifting heavy materials, operating heavy machinery, and prolonged manual labor[16]. Moreover, the nature of construction work often involves working in challenging environments, such as extreme temperatures, heights, or confined spaces. This exacerbates the physical strain experienced by workers[17] and leads to physical fatigue.

Fatigue on construction sites carries both significant safety and productivity implications. From a safety standpoint, according to Namian et al.[18] fatigued workers tend to exhibit lower hazard detection and risk perception abilities than their non-fatigued counterparts, which reduces safety on construction sites. Moreover, physical fatigue affects the ability of workers to react to and confront hazards and increases the likelihood of accidents[19]. According to Parijat and Lockhart[20], fatigue causes 40% of slip-induced falls on construction sites. From a productivity standpoint, according to several researchers, fatigue negatively affects productivity, leading to delays and cost overruns. Through a correlation analysis, O'Neill and Panuwatwanich[4] determined a negative association between fatigue and the level of productivity. Additionally, through productivity analysis, they found that the average cost due to fatigue-based decreased production rates was $50,000 per year for a concrete crew of ten members. Similarly, in 2015, the Bureau of Labor Statistics reported that non-fatal accidents in construction due to fatigue required a median of 13 days from work[21].

To mitigate the consequences of fatigue on construction sites, traditionally, project managers relied solely on survey-questionnaire-based methods (such as Borg's scale and NASA-TLX) to assess fatigue[22, 23]. Such survey-questionnaire-based methods have been advantageous in assessing fatigue. However, they rely on self-reports, which can be subjective and influenced by factors such as social desirability bias or the reluctance of workers to admit feeling fatigued[24]. Additionally, conducting and analyzing surveys can be time-consuming and may not provide real-time insights into the fatigue levels of workers[9].

Recent advancements in wearable physiological sensing technology (miniaturization of sensing modules, portability, and comfort[10]) coupled with advancements in information processing and big data analysis facilitate the non-invasive monitoring of physical fatigue among construction workers in real time[25]. Several studies have demonstrated the potential of wearable physiological sensors for monitoring the physical fatigue of construction workers, with promising results in terms of both accuracy and feasibility[11, 12, 26]. These sensors offer continuous monitoring capabilities, enabling the timely detection of fatigue onset and the implementation of proactive intervention strategies. Moreover, their non-invasive nature ensures minimal disruption to their tasks and workflow, which enhances their practical utility on construction sites. However, individual physiological differences and responses to work demands are the critical challenges in accurate and reliable fatigue detection. For instance, Umer et al.[27] observed that inter-individual factors influenced HRV and respiration rate among participants in their study. Similarly, Aryal et al.[12] found that the inclusion of personal features, such as age, weight, and body mass index (BMI), significantly improved the accuracy of their physical fatigue prediction model. These findings highlight the limitations of current one-size-fits-all approaches to fatigue detection, which often rely on generic threshold values for models that might not be accurate for all individuals. This can lead to misinterpretations of physiological signals and missed warnings, potentially compromising the effectiveness of fatigue management strategies at construction sites. Therefore, the influence of inter-individual variability on physiological responses to fatigue needs to be understood. In this study, we investigated the impact of various inter-individual factors, namely weight, height, and BMI, on physiological responses to fatigue.

3. METHODOLOGY

3.1. Experiment Design

An experiment was designed to achieve the research objective. Subjects were asked to complete simulated physically demanding construction tasks to transition from a non-fatigued to a fatigued state. EDA signals and heart rate were recorded alongside their corresponding levels of fatigue according to the rate of fatigue (ROF) scale. The influence of inter-individual factors on EDA signals and heart rate responses to fatigue during construction tasks was investigated using correlation analysis.

3.2. Subjects

A total of ten healthy males volunteered for the study. The participants were students aged between 19 and 33 (M = 25.5 years; SD = 4.1 years). The participants were asked to refrain from alcohol and caffeine intake and to get sufficient sleep 24 hours prior to partaking in the experiment.

3.3. Experiment Task

The participants were asked to complete simulated material handling tasks, which involved transporting a 25 kg bag of cement from the second to sixth floors repeatedly for 20 min and transporting and arranging formwork over a distance of 10 m for 40 min. ROF was adopted to measure the physical fatigue levels of the participants. The ROF scale quantifies subjective fatigue feedback on the feeling of tiredness while performing physically demanding tasks[28].

3.4. Data Analysis

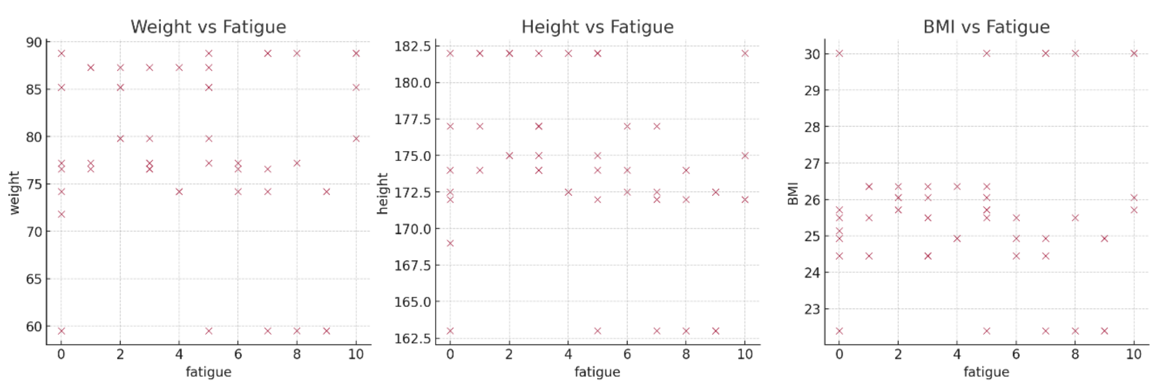
The experimental data was manually processed through the selection of EDA and heart rate (BPM) signals corresponding to fatigue levels, alongside the height, weight, and BMI of the participants. Subsequently, the data was imported into MATLAB for analysis. An exploratory data analysis, coupled with a simple predictive modeling approach, was employed to explore the influence of the inter-individual features (weight, height, and BMI) on fatigue prediction. Appropriate metrics, such as R-squared (R2) and mean squared error (MSE), were used to assess model performance. Additionally, correlation analysis was conducted to examine the interaction between the inter-individual features and EDA. A random forest model analysis was also employed to evaluate feature importance. Finally, feature engineering techniques were applied to further investigate the effect of inter-individual factors in enhancing model performance.

4. EXPERIMENT AND RESULTS

4.1. Inter-individual features vs Fatigue

The linear regression model incorporating the inter-individual features and fatigue yielded an MSE of approximately 14.62 and an R2 of -0.33. *Figure 1* shows the comparison between all inter-individual features against fatigue but does not clearly demonstrate a relationship with fatigue. This suggests that the predictive power of these features may be limited.

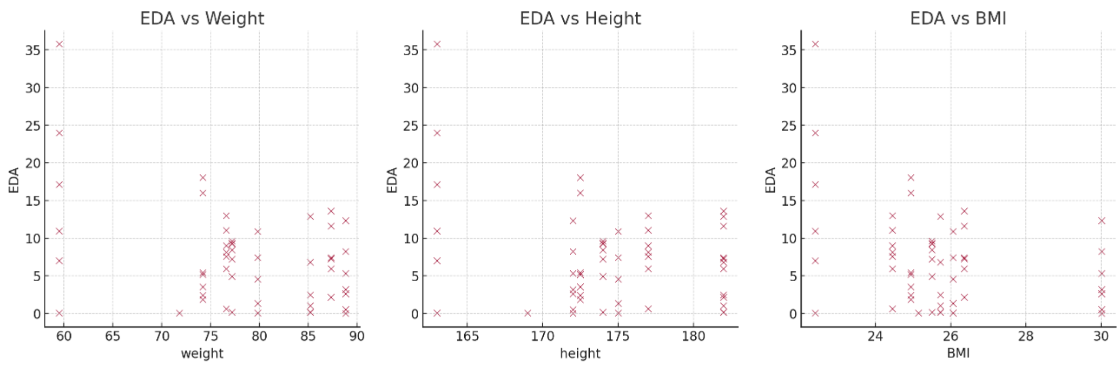
Figure 1. Scatter plots of inter-individual features vs fatigue



4.2. Inter-individual features vs EDA

EDA and weight showed a correlation coefficient of approximately -0.4, indicating a moderately negative relationship. As weight increased, EDA tended to decrease. EDA and height showed a correlation coefficient of approximately -0.32, suggesting a weak to moderately negative relationship. EDA and BMI showed a correlation coefficient of approximately -0.36, indicating a moderately negative relationship. The correlation values and scatter plots in *Figure 2* provide insights into the relationship between EDA and inter-individual features.

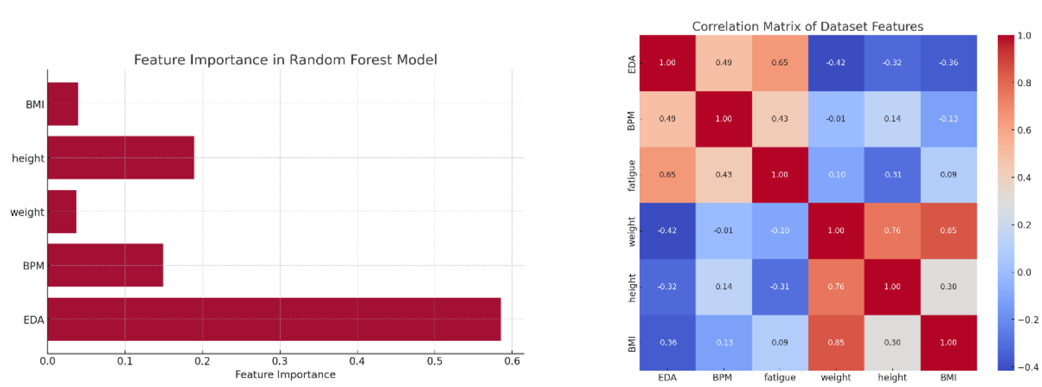
Figure 2. Scatter plots of inter-individual features vs EDA



In the random forest model, the number of trees and random seed hyperparameters were set to 100 and 42, respectively. The MSE of the random forest (approximately 6.18) was lower than that of the linear regression model, indicating better predictive performance. Additionally, the R2 value is ≈0.44. This suggests that approximately 44% of the variance in fatigue can be explained by the model. This represents a significant improvement over the linear regression model.

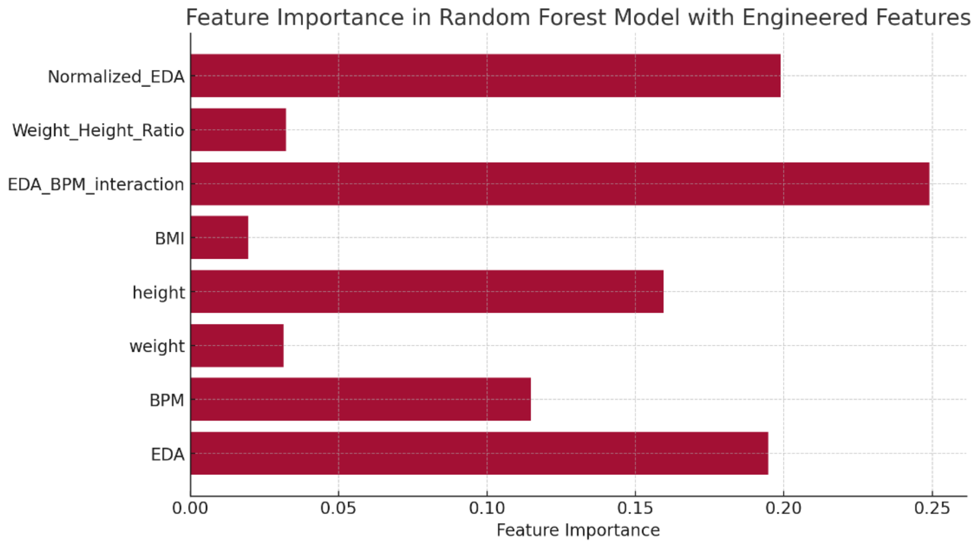
Figure 3(a) displays a bar chart indicating the importance of each feature. The chart indicates a strong correlation between EDA and fatigue. Heart rate (BPM) and weight were also identified as important features, although to a lesser extent than EDA. Conversely, height and BMI exhibited the least influence on the model, implying their slight significance in predicting fatigue in this dataset. *Figure 3(b)* represents a correlation matrix depicting the relationship between all features.

Figure 3(a)(b). Bar chart showing feature importance(left) and correlation matrix of all features(right)



Finally, feature engineering was performed by combining features to form new metrics; then, the random forest model was retrained with the same hyperparameters. The MSE for the new model with engineered features was approximately 5.99, slightly lower than that of the previous model (6.81). The R2 value increased to approximately 0.46 from 0.44 in the previous model. This suggests a minor improvement in the ability of the model to explain the variance in fatigue. *Figure 4* shows the feature importance in the random forest model with engineered features.

Figure 4. Bar chart showing features importance of engineered features.



5. DISCUSSION

In the linear regression analysis, the inter-individual features, such as weight, height, and BMI, did not serve as strong predictors of fatigue based on the findings of this experiment. The negative R2 value indicated that the model had poor predictive ability, suggesting that these features fail to capture sufficient variance in fatigue levels. EDA tended to decrease as the inter-individual feature values increased. This implied a potential influence of individual physical characteristics on EDA levels. The strength of these relationships was moderate to weak. Other factors within these features may also have affected EDA. Hence, conducting further analysis, possibly involving additional features, could yield a more comprehensive understanding of the interaction of these factors with EDA.

Moreover, the random forest model offered a more insightful and accurate prediction of fatigue than the linear regression model. Notably, height emerged as an important feature with relatively moderate importance. This could potentially be attributed to the limited number of training samples within the dataset. Additionally, the integration of engineered features slightly enhanced the predictive capability of the model. For instance, the “Weight_Height_Ratio” feature exhibited greater significance than BMI. This suggests that a meaningful combination of features can capture finer nuances in the relationship between various factors and fatigue.

6. CONCLUSION

Based on the findings of this study, the inter-individual features evidently influence physiological signals and ultimately fatigue prediction. Thus, the incorporation of engineered features can enhance the predictive performance of fatigue models. Specifically, the observed negative relationship between EDA and the inter-individual features suggested a potential influence of individual physical characteristics on EDA levels, underscoring the importance of considering such factors in fatigue prediction.

Future studies should focus on exploring additional personal physical characteristics and their impact on physiological signals related to fatigue. Furthermore, the integration of larger and more diverse datasets, along with sophisticated feature engineering techniques, could further improve the accuracy and robustness of fatigue prediction models.

Overall, this research contributes to advancing our understanding of the complex interplay between inter-individual features, physiological signals, and fatigue prediction. By addressing these areas, researchers can develop more effective strategies for fatigue management and promote the health and safety of workers at construction sites.

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