Vision Transformer-based Local Physical Fatigue Assessment using Electromyography (EMG) Signals for Construction Worker Health Monitoring

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Abstract

Construction workers frequently endure high levels of physical strain, which can lead to fatigue and long-term musculoskeletal disorders. Traditional methods of fatigue assessment often fail to provide timely and accurate diagnoses, particularly in dynamic work environments. In this paper, we present a Vision Transformer-based approach for assessing localized physical fatigue using Electromyography (EMG) signals. This method leverages the high learning capacity of Vision Transformers to capture both spatial and temporal features from EMG data, enabling precise detection and prediction of fatigue. By focusing on specific muscle groups that are prone to fatigue during construction tasks, our model delivers detailed insights into the onset of fatigue at a localized level. Experimental evaluations conducted on roofing tasks targeting the biceps brachii and brachioradialis demonstrate that the proposed method can predict fatigue to a localized level. The results demonstrate the potential of this approach for enhancing on-site health monitoring systems and establishing a foundation for proactive interventions aimed at reducing the risk of fatigue-induced injuries among construction workers.

Keywords –

EMG ; Vision Transformer; CNN; Fatigue Detection

1 Introduction

Physical fatigue is a critical factor influencing worker productivity, health, and safety in various industries such as manufacturing, construction, and logistics [1]. Workers exposed to prolonged or repetitive physical tasks often experience muscle fatigue, which can impair motor control, reaction times, and cognitive function. This leads to a heightened risk of injuries and accidents, particularly in jobs that involve lifting, repetitive movements, or prolonged exertion [2]. Given the high stakes, detecting and managing physical fatigue in real-time is vital for reducing workplace injuries and ensuring worker well-being [3].

Accurately assessing physical fatigue remains a challenging problem due to its subjective nature and the variability in how it manifests across different individuals. Traditional fatigue assessment methods, such as self-reported surveys (e.g., Borg Fatigue Scale) or physical performance tests, are limited by their inherent subjectivity and time-consuming nature [4,5]. Moreover, these methods often fail to capture real-time changes in muscle fatigue, making them impractical for dynamic, high-risk environments where quick decision-making is crucial.

Electromyography (EMG) is an objective method for assessing muscle activity by measuring the electrical signals generated by muscle contractions. As muscles fatigue, changes occur in both the amplitude and frequency of the EMG signals, making it possible to quantify muscle fatigue objectively [6]. However, analyzing EMG data for fatigue detection presents challenges due to the complex, non-linear nature of the signals, the presence of noise, and variability caused by different muscle groups, task conditions, and individual characteristics.

In recent years, machine learning (ML) has emerged as a promising approach for analyzing complex bio-signals, including EMG [7]. By learning patterns from data, ML models can detect subtle changes in EMG signals associated with muscle fatigue. Despite the promise of ML, traditional models such as support vector machines and convolutional neural networks rely heavily on manual feature extraction and are often limited by their inability to capture long-range dependencies in the data, particularly in time-series signals like EMG.

Transformers, originally developed for natural language processing, have gained attention in the field of computer vision due to their powerful ability to capture global dependencies within input data [8]. The Vision Transformer (ViT), in particular, has shown state-of-the-art performance on various image classification tasks. Unlike traditional CNNs, which use localized filters to extract features, the ViT relies on a self-attention mechanism to capture both local and global features from input images or 2D data. This makes ViTs particularly well-suited for analyzing spectrograms of EMG signals, where capturing both temporal and frequency information is crucial for fatigue detection.

One of the key challenges in applying ML models to EMG data is the variability and noise present in time-domain signals. By transforming EMG signals into spectrograms (time-frequency representations), it becomes possible to extract both temporal and spectral features from a single representation [9]. This approach not only reduces noise but also enhances the model's ability to detect tempo-spectral patterns in the data and provides image representation which can directly processed by the ViT without any manual feature extraction. As ViTs can model both local and global context in EMG spectrograms, it makes them well-suited for distinguishing between different levels of physical fatigue.

In this paper, we propose a Vision Transformer-based approach for assessing local physical fatigue using EMG signals. The method involves converting EMG signals into spectrograms, which are then input into a fine-tuned Vision Transformer model for classification. The objective is to demonstrate that this approach can effectively classify different levels of fatigue (low, medium, high) with higher accuracy and robustness compared to traditional machine learning techniques. By leveraging the power of the ViT model, we aim to provide a scalable, real-time solution for fatigue monitoring, particularly in labor-intensive work environments.

2 Background and Related Work

2.1 EMG and Fatigue Assessment

Electromyography (EMG) has emerged as a crucial technique for evaluating muscle activity by capturing electrical signals generated during muscle contractions. This method offers direct insights into muscle activation patterns and serves as a valuable tool for assessing muscle fatigue [10]. As muscles experience fatigue, EMG signals undergo characteristic changes, including amplitude increases and frequency decreases, reflecting the underlying physiological processes such as metabolic byproduct accumulation and additional motor unit recruitment. The analysis of EMG signals for fatigue detection involves a multi-step process:

1. Signal preprocessing (filtering, normalization)
2. Feature extraction
3. Pattern recognition

Traditional approaches have relied on signal processing methods like Fourier and Wavelet Transforms for feature extraction. However, these techniques often require manual feature selection and struggle to capture the complex, non-linear patterns associated with muscle fatigue [4]. Furthermore, EMG signals are susceptible to various sources of noise and artifacts, including movement and electrode displacement, which complicate the analysis process. Time-frequency domain analysis, particularly through the use of spectrograms, has gained traction as an effective method for representing EMG signals. Spectrograms offer a visual depiction of a signal's frequency content evolution over time, facilitating the identification of fatigue-related patterns. This representation not only enhances the interpretability of EMG data but also paves the way for the application of advanced machine learning techniques in fatigue classification. Recent advancements in machine learning have opened new avenues for EMG signal analysis: Deep Learning Models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown promise in automatically extracting relevant features from raw EMG data. Ensemble methods such as combining multiple classifiers has demonstrated improved robustness and accuracy in fatigue detection. On the other hand, transfer learning methods leveraging pre-trained models on large datasets has enabled more efficient training on smaller, task-specific EMG datasets [11–13].

Despite these advancements, challenges remain in developing localized fatigue assessment methods for diverse muscle groups and tasks. The integration of EMG-based fatigue detection systems into practical workplace settings, particularly in dynamic environments like construction sites, presents additional hurdles that require innovative solutions.

2.2 Machine Learning for Fatigue Classification

Machine learning (ML) has revolutionized the analysis of complex bio-signals, particularly EMG, for physical fatigue detection and classification. The field has evolved from traditional ML approaches to sophisticated deep learning methods, each offering unique advantages in processing EMG data [14].

Early efforts in EMG-based fatigue classification relied on conventional ML algorithms such as Support Vector Machines (SVM), Random Forests, and Decision Trees [15]. These methods demonstrated varying degrees of success in handling high-dimensional data and non-linear classification problems [16].

The advent of deep learning has significantly improved EMG signal analysis. Convolutional Neural Networks (CNNs) have shown exceptional performance in automating feature extraction from raw or minimally processed EMG data. Liu et al. proposed a hybrid CNN-LSTM model that outperformed standalone LSTM, CNN, and RF models approaches in muscle fatigue recognition [17]. Long Short-Term Memory (LSTM) networks have also demonstrated promise in capturing temporal dynamics in EMG signals, with a study by Wang et al. developing an LSTM-based muscle fatigue recognition model that surpassed CNN and SVM in classification performance [18].

Despite these advancements, several challenges persist in EMG-based fatigue classification. These include the generalizability of models across different tasks and individuals, the ability to capture long-range dependencies in EMG signals, and the development of real-time processing capabilities for dynamic work environments. Recent developments aim to address these challenges through hybrid models, time-frequency analysis, and transfer learning approaches [7].

The field is moving towards more sophisticated and integrated approaches, including multi-modal analysis combining EMG with other physiological signals, the development of explainable AI for better interpretation of model decisions, and adaptive learning techniques that can adjust to individual differences and changing conditions in real-time. As research progresses, the integration of advanced ML techniques with domain-specific knowledge in physiology and biomechanics promises to yield more accurate, robust, and practical solutions for EMG-based fatigue detection and classification, particularly in dynamic work environments such as construction sites.

2.3 Vision Transformers and Bio-signals

Vision Transformers (ViTs) represent a significant leap forward in deep learning, particularly in computer vision tasks. Unlike traditional Convolutional Neural Networks, ViTs leverage the Transformer architecture's self-attention mechanism to capture both local and global dependencies within input data. This unique approach allows ViTs to model complex spatial relationships and long-range interactions, making them highly effective for tasks that require a comprehensive understanding of the entire input [19]. In the realm of bio-signal processing, especially for EMG-based fatigue detection, ViTs offer several compelling advantages. By leveraging EMG spectrograms—images representing time-frequency information [20]—ViTs can directly analyze temporal and spectral information in EMG signals. Their ability to process and understand 2D spectrograms makes them well-suited for identifying subtle changes in EMG signals that correlate with different levels of muscle fatigue. Moreover, the global context capture capability of ViTs enhances their robustness against noise and variability in EMG data, potentially leading to more accurate and reliable fatigue classification.

Recent literature has demonstrated several applications of transformer-based architectures in bio signal processing [21][22].

These advancements suggest that transformer-based models, including ViTs, have significant potential in bio-signal processing. Their ability to capture complex spatial and temporal relationships in data makes them particularly suitable for analysing EMG signals for fatigue detection. This work leverages the advancements in ViT and electromyography techniques to develop framework for localized fatigue estimation in construction workers.

3 Methodology: ViT-based Fatigue Assessment

The proposed methodology for EMG-based fatigue assessment consists of three main parts: data acquisition, spectrogram generation, and fatigue classification using a Vision Transformer (ViT) model. In the first stage EMG signals is acquired from the muscle group of interest using surface electrodes, and bio-amplifier. These signals are then processed, which includes labeling

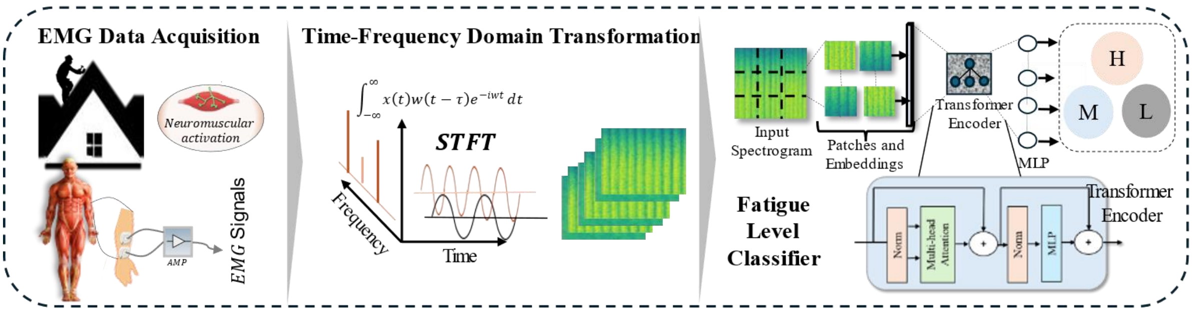

Figure 1: Overview of the methodology. The acquired EMG signals are converted to spectrograms using STFT

which is then used as input to the Vision Transformers model.

and windowing. For labeling, the Borg Fatigue rating scale is employed, providing a standardized measure of perceived exertion. This step is crucial for creating a labeled dataset that can be used to train and evaluate the Vision Transformer model. The acquired signals is used to generate a spectrogram through short-time Fourier transform. The generated spectrogram is then used as input to the Vit model which then leverages transformer architecture to classify between low, medium and high levels of fatigue (Figure 1).

3.1 Spectrogram Generation

The second phase involves transforming the time-domain EMG waveforms into 2D spectrograms using the Short-Time Fourier Transform (STFT). The STFT is defined by the equation 1:

$$STFT\{x\}(\tau,\omega) = X(\tau,\omega) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-iwt}dt \tag{1}$$

Where, x represents the raw EMG signals in the time domain, and w(t) is a non-zero window function. This transformation allows for the visualization of frequency changes over time, providing a richer representation of the EMG data compared to the raw time-domain signal. The use of spectrograms offers several significant advantages in EMG signal analysis. Firstly, it captures both temporal and spectral information in a single representation, allowing for a comprehensive view of the signal's characteristics. Secondly, the spectrogram transformation effectively reduces noise and enhances relevant features in the EMG signal, improving the signal-to-noise ratio and facilitating more accurate analysis. Lastly, by converting the EMG data into a 2D image-like format, spectrograms enable the application of powerful image processing techniques to bio-signal data, opening up new possibilities for advanced analysis and feature extraction.

3.2 Fatigue Classification using Vision Transformer

The final stage involves using the generated spectrograms as input to a Vision Transformer (ViT) model for fatigue level classification. The ViT model, pre-trained on the ImageNet-21K dataset , is fine-tuned for the specific task of EMG-based fatigue detection. b Key aspects of the ViT model include:

Self-Attention Mechanism: The model uses self-attention to process the entire spectrogram as a sequence of tokens, capturing long-range dependencies and global context. This is particularly beneficial for understanding complex spatial relationships in the spectrograms.

Model Architecture: The ViT consists of multiple Transformer blocks, each comprising self-attention and feedforward layers. The self-attention mechanism is mathematically expressed as 2:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

where Q, K, and V denote the query, key, and value matrices derived from input embeddings, and d_k represents the dimensionality of the key vectors.

Feedforward Neural Networks: Each Transformer block incorporates feedforward neural networks to further process token embeddings:

Fine-tuning Process: The pre-trained ViT model is adapted to the specific task of EMG-based fatigue classification through fine-tuning on a acquired dataset of EMG spectrograms (roofing tasks).

Loss Function: The model is trained using categorical cross-entropy as the loss function (Equation 3).

$$H\big(g_f(I_{2D})\big) = -\sum_{j=1}^{k} y_j \log\,(g_f(I_{2D})) \tag{3}$$

Here g_f is the ViT model where whereas I_{2D} is the input 2D spectrogram, y_j represents true label of the class whereas k represents the number of classes.

By using spectrograms as an intermediate representation, the approach makes the use of power architecture like ViT feasible for time-series-based EMG signals.

4 Experimental Case Study

The experimental study was designed to comprehensively assess muscle fatigue in construction workers through EMG signal analysis. Twelve volunteers were recruited to participate in a carefully controlled experimental protocol that simulated realistic construction tasks, specifically focusing on roofing activities that engage the upper limb muscle groups. The participant selection process made sure that all subjects were free from medical conditions that could potentially interfere with the experimental measurements.

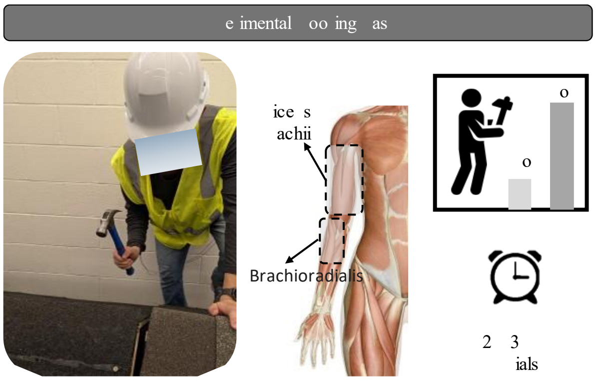

Figure 2: Roofing task was used to evaluate performance of the developed framework. Subjects hammered shingles into the roof structure during the task when EMG signals were acquired.

Electrode placement was a critical aspect of the methodology. Specialized surface EMG electrodes were positioned bilaterally over the biceps and brachioradialis muscle group. A multichannel ADInstruments bio-amplifier was utilized to acquire high-resolution EMG signals, with a sampling frequency of 1 kHz and a window size of 3 seconds. A sliding window of 1 seconds was used for the signal's segmentation. The average time of experimentation was around 12 minutes per subject excluding setup and rest periods. The generated spectrograms were split into 80:20 rationfor training and testing with a stratified split to make it consistent across all the classes.

The electrode configuration allowed for precise tracking of muscle electrical activity during various physical tasks. The Borg Rating of Perceived Exertion (RPE) scale played a crucial role in fatigue classification. This well-established subjective measure allows participants to rate their perceived level of physical exertion on a scale typically ranging from 6 to 20. In this study, the RPE was used to categorize fatigue levels into three distinct classes: low, medium, and high. Participants were trained to provide self-assessments, ensuring the reliability of the subjective fatigue ratings.

The experimental tasks were carefully designed to simulate real-world construction scenarios, with a particular focus on roofing activities. Participants performed controlled roofing tasks that engaged the biceps brachii and brachioradialis muscles, mimicking the physical demands of actual construction work. The tasks were structured to progressively induce muscle fatigue, allowing to capture the nuanced changes in muscle activation patterns over time (using a hammer of increased load). Signal processing played a critical role in transforming raw EMG data into meaningful insights. The acquired signals underwent several preprocessing steps, including filtering to remove noise, normalization to account for variations and transformation into spectrograms using Short-Time Fourier Transform (STFT). This approach converted time-domain signals into two-dimensional representations that could be effectively analysed using the Vision Transformer model. From twelve subjects with

During the experiment, participants were given adequate rest periods between tasks to minimize cumulative fatigue effects and ensure the reliability of the measurements. By integrating objective EMG measurements with subjective fatigue ratings, the study aimed to develop a comprehensive understanding of muscle fatigue in construction workers.

5 Results and Discussion

The developed fatigue estimation model based on a Vision Transformer (ViT) network demonstrated promising performance in classifying fatigue levels using EMG signals from the biceps brachii and brachioradialis muscles. The model's performance varied across different muscle groups, with distinct patterns observed

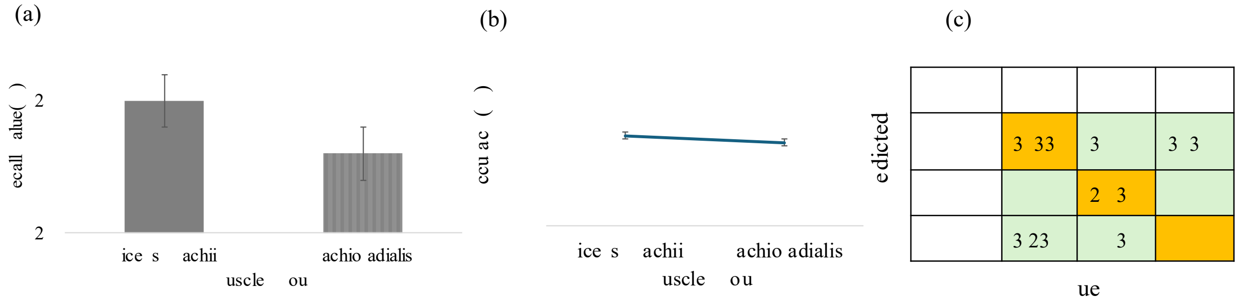

Figure 3: (a) Bar diagram for recall value for the high fatigue estimation. (b) Accuracy for fatigue estimation. (c) Confusion matrix for the fatigue estimation through ViT.

in fatigue detection accuracy.

For high fatigue estimation, the recall values showed notable differences between muscle groups, with biceps brachii achieving approximately 82% recall and brachioradialis showing around 78% recall. The overall fatigue detection accuracy remained relatively consistent across both muscle groups, with values around 75% (biceps brachii- 76% and brachioradialis – 74%).

The model showed the strongest performance in identifying low fatigue states (83.3% accuracy) , followed by high fatigue states (80.65% accuracy), while medium fatigue states presented the most challenging classification task (72.73% accuracy). This pattern suggests that the transition between fatigue states, particularly in the medium range, requires careful consideration in future model refinements. The superior performance of the ViT model can be attributed to its ability to capture global context through the analysis of spectrograms. By transforming EMG signals into time-frequency representations, the model leverages its strength in processing two-dimensional data, which allows it to identify subtle changes in muscle activation associated with varying levels of fatigue. The advantages of using spectrograms as input for the ViT model remain significant, facilitating comprehensive analysis of both temporal and spectral features. This multi-dimensional approach enhances the model's ability to assess fatigue accurately across different muscle groups and fatigue states.

For a more comprehensive analysis, the authors also compared the manual feature extraction-based method using both time domain feature (Signal Mean Absolute Value and Root Mean Square) and frequency domain feature (Median Frequency (MDF) and Mean Frequency (MEF) [5] and trained a SVM, ANN, and random forest models from the extracted features. The SVM model provided an average accuracy of 59.4%, which was the highest among the competing model. Table 2 outlines the average accuracy and its comparison with the ViT model.

Table 1: Comparison with ML models using manually extracted feature from EMG signals

Model	Accuracy	% improvement in VIT
SVM	59.4 %	26 %
ANN	51.2 %	46 %
Random Forest	58.1 %	29 %

While the developed mode is able to predict localized fatigue levels with a decent accuracy, several challenges and limitations remain. Real-time processing capabilities are crucial for practical applications, and while our model shows promise, further optimization may be necessary to ensure efficiency in resource-constrained environments. Additionally, variability across participants can affect performance; individual differences in muscle composition and fatigue response patterns may lead to inconsistent results. Moreover, a larger and more diverse dataset would likely improve the robustness of the model.

Looking ahead, there are several promising avenues for future research. Exploring transfer learning from larger biomedical datasets could enhance the model's performance by providing additional training data that captures a wider range of muscle activity patterns. Moreover, integrating multi-modal data—such as heart rate and skin temperature—could offer a more comprehensive view of fatigue status, potentially improving detection accuracy. Investigating adaptive learning techniques may also allow for personalization of the model for individual users, further enhancing its applicability across diverse populations.

Overall, our study highlights the potential of deep learning integrated EMG-based models for localized fatigue detection in physically demanding environments such as construction sites. By addressing current limitations and exploring future directions, we aim to develop a robust system that can contribute significantly to worker safety and productivity through effective fatigue monitoring.

6 Conclusions

This study presents a novel approach for local physical fatigue assessment using a Vision Transformer-based model applied to EMG spectrograms. The developed system demonstrates significant potential for real-time fatigue monitoring in occupational settings, particularly in dynamic environments such as construction sites. With an achieved accuracy of 75% and and recall of over 80%, our model outperforms traditional machine learning approaches in classifying different levels of muscle fatigue. The success of this ViT-based approach highlights the advantages of leveraging advanced deep learning techniques for bio-signal processing. By capturing both spatial and temporal features from EMG data, the model provides a more nuanced understanding of fatigue progression, crucial for timely interventions in workplace safety. The use of spectrograms as input to the ViT model proved particularly effective, allowing for a comprehensive analysis of muscle activation patterns associated with fatigue. The implications of this research extend beyond mere performance metrics. Accurate and real-time fatigue detection systems have the potential to revolutionize workplace safety practices. By enabling proactive interventions, such systems can help prevent injuries, optimize task assignments, and improve overall worker health outcomes. The integration of such technology into existing ergonomics programs and fatigue management systems could lead to significant improvements in workplace safety and productivity. However, this study also acknowledges several limitations and areas for future research. Expanding the dataset to include a more diverse range of participants and occupational tasks will be crucial for enhancing the model's generalizability. Future work should also explore the integration of multi-modal data and further optimize real-time processing capabilities. Additionally, addressing ethical considerations and privacy concerns will be essential for the widespread adoption of such monitoring systems in workplace environments. In summary, this research represents a significant step forward in the field of occupational health and safety, offering a promising tool for real-time fatigue assessment. As we continue to refine and expand upon this approach, the potential for creating safer, more productive work environments becomes increasingly tangible, underscoring the importance of continued research and development in this critical area.

Acknowledgments

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