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Design of flexible polyimide-based serpentine EMG sensor for AI-enabled fatigue detection in construction

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ABSTRACT

Physical fatigue and musculoskeletal disorders are critical health issues for construction workers, stemming from repetitive motions, heavy lifting, and awkward postures. These factors compromise worker well-being, productivity, and safety while increasing the risk of accidents and long-term health problems. Recent advancements in wearable health monitoring technology offer potential solutions, but current sensors encounter significant challenges in the dynamic construction environment. These include inadequate skin contact, increased contact impedance, and vulnerability to motion artifacts all of which degrade signal quality and reduce the accuracy of fatigue detection. This paper develops a fractal-based, flexible sensor for enhanced adaptability and accurate fatigue estimation. Finite element analysis compared five space-filling designs, with the serpentine curve exhibiting the highest contact area and lowest strain, making it the preferred choice for fabrication. Evaluations demonstrated significant improvements in signal-to-noise ratio (SNR) and motion artifact reduction, with the newly developed sensor achieving a 37 % to 59 % SNR improvement over commercial electrodes across different muscle groups. The developed flexible sensor was integrated with a fatigue-detecting framework based on a vision transformer model which provided an average accuracy of 87 % for fatigue detection. The developed sensor significantly enhances EMG signal quality and reliability, promising improved health monitoring and safety for construction workers.

1. Introduction

Physical fatigue and musculoskeletal disorders represent significant health concerns for construction workers, stemming from the repetitive motions, heavy lifting, and awkward postures inherent in their tasks [1,2]. These factors contribute to muscle fatigue and related musculoskeletal issues, compromising worker well-being. The consequences of physical fatigue extend beyond immediate discomfort, impacting efficiency, cognitive function, and work quality [3]. On one hand, the quality of life of a construction worker is compromised while on the other hand, there is a loss of productivity and corresponding economic losses pertaining to absences and medical bills. Moreover, sustained fatigue increases the risk of accidents, diminishing both workplace safety and the quality of life for workers [4]. Furthermore, chronic fatigue has been linked to long-term health problems, including heart disease, carpal tunnel syndrome, high blood pressure, tendonitis, and depression [5].

Recent advancements in computing technology, material science, and artificial intelligence have fueled the development of wearable health monitoring and point-of-care systems, making continuous health monitoring both accessible and scalable. Compact, wearable devices have been successfully commercialized for diverse applications, including blood glucose sensing, cardiovascular monitoring, and sleep tracking [6,7]. Prior research has explored the potential of various physiological signals – such as photoplethysmography (PPG), electroencephalography (EEG), electrocardiogram (ECG), and electromyography (EMG) – as biomarkers to assess a wide range of health concerns, including physical fatigue, heat stress, cognitive load, and mental stress [8–11]. Real-time access to this health information can assist workers and managers to take proper preventive measures to optimize worker health, and productivity, and reduce downtime [12]. Among these signals, electromyography (EMG) stands out as particularly relevant for assessing physical fatigue due to its ability to directly measure muscle activity and provide insights into fatigue levels and muscular strains [13].

While recent strides in research have showcased promising advancements in wearable health monitoring [12], the integration of such technology within the construction industry lags significantly behind.

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Despite the rapid evolution of algorithms and data analytics, a critical bottleneck persists in the form of sensor technology [14]. The current array of sensors predominantly relies on off-the-shelf products designed for clinical or general purposes, lacking the tailored adaptability required for construction environments.

The inflexibility of these sensors is a primary limitation, hindering their efficacy in construction settings. Typically constructed from inflexible materials like plastics or metals, these sensors struggle to adapt to the dynamic movements and complex contours of the human skin during construction tasks. This lack of flexibility exacerbates numerous issues. For instance, poor skin contact leads to increased contact impedance [15], resulting in air gaps that elevate electrical resistance and compromise signal quality. Additionally, motion artifacts occur when the sensor detaches or shifts position in response to movement, introducing noise and distortions into the physiological signals [16]. Moreover, discomfort arises from sensors digging into the skin, causing irritation and hindering prolonged wear, especially in areas subject to high movement or pressure [17].

Furthermore, hydration management presents a significant challenge in construction environments, where high temperatures often lead to profuse sweating [18,19]. Traditional sensors lack adequate breathability or sweat absorption capabilities, resulting in signal degradation as electrolytes in sweat alter signal conductivity, thus distorting data accuracy. Compromised adhesive properties in the presence of excessive moisture also contribute to sensor detachment, jeopardizing continuous monitoring. Additionally, trapped sweat can cause skin irritation and rashes, particularly among users with sensitive skin, further exacerbating discomfort and potential health risks [17].

Building upon these identified challenges, this paper develops a fractal-based, flexible sensor with a dedicated local fatigue estimating framework. Departing from the inflexibility of traditional sensors, this design prioritizes flexibility and adaptability, ensuring enhanced conformity to the skin's natural contours. By mitigating issues such as contact impedance and motion artifacts, inherent in conventional sensors, this fractal-based approach can reduce motion artifacts while increasing the accuracy of fatigue estimation framework which can contribute to overall health monitoring in construction environments.

The paper is structured as follows: Section 2 offers a review of relevant literature, concentrating on wearable health monitoring, motion artifacts, and flexible sensors. Section 3 delineates the proposed methodology, elucidating the technical intricacies of the sensor design and fabrication process as well as data acquisition and fatigue assessment techniques. In Section 4, a detailed case study is presented, encompassing the experiments conducted to evaluate the framework. The findings are presented upon in Sections 5 and 6. Finally, Section 7 presents the concluding remarks of the paper.

2. Related work

2.1. Wearable physiological sensing in construction

The rapid evolution of wearable health monitoring technology, driven by miniaturization and advancements in sensor design, holds immense potential to transform various industries, including the demanding field of construction. These compact, body-worn devices enable continuous, real-time measurement of diverse physiological parameters, offering insights into health status, stress levels, and overall well-being [20]. Initially developed for clinical settings, wearable sensors have expanded into athletic performance optimization, personalized health tracking, and occupational safety monitoring [21].

Within the construction industry, wearable physiological sensing presents a compelling solution for proactively addressing complex health and safety challenges [12]. Construction workers face a unique set of risks, including physical fatigue, musculoskeletal disorders, heat stress, and cognitive decline, often exacerbated by strenuous tasks, dynamic work environments, and exposure to environmental hazards [9]. By monitoring physiological indicators such as heart rate variability, blood volume pulse, muscle activity, brain signals, galvanic skin response, skin temperature, etc. wearable sensors can provide early warnings of overexertion, impending heat stress, and declining cognitive function [22,23]. For instance, in a recent work, Ojha et al. developed XGBoost-based framework to estimate heat stress levels in construction workers based on PPG, EDA, and EEG signals [24]. This real-time data can empower workers and managers to implement timely interventions, optimize work-rest schedules, and adapt safety protocols, ultimately promoting a healthier, safer, and more productive construction workforce.

Despite these advancements, significant knowledge gaps remain in the application of wearable physiological sensing in construction. Current sensor technologies often lack the necessary flexibility and robustness for dynamic construction environments, leading to issues such as poor skin contact, increased contact impedance, and motion artifacts. Furthermore, there is a need for more tailored algorithms and models that can accurately interpret the physiological data specific to the physical demands and stressors of construction tasks. Addressing these gaps is crucial for enhancing the reliability and efficacy of wearable health monitoring systems in improving worker health and safety.

2.2. Electromyography and health monitoring

Electromyography offers a powerful non-invasive method for assessing muscle function and health. At its core, EMG measures the bioelectrical potentials generated during muscle contractions. These potentials originate from the depolarization of muscle fibers as they receive signals from motor neurons [25]. WMSDs represent a prevalent concern in the construction industry, stemming from repetitive motions, forceful exertions, and awkward postures [26]. EMG provides a valuable window into muscle fatigue, a key contributing factor to WMSDs. By monitoring changes in EMG signal characteristics, it's possible to identify early signs of fatigue and assess the risk of potential injuries [27].

Various signal analysis techniques allow for the extraction of meaningful fatigue-related information from raw EMG data. Changes in amplitude, such as root mean square or mean absolute value, can reflect decreasing force production as muscles fatigue. Frequency domain analysis, like power spectral density, reveals shifts in the EMG spectrum towards lower frequencies during fatiguing contractions [28,29]. Additionally, time-frequency analysis methods, such as wavelet transforms, offer insights into the dynamic evolution of fatigue over time. For instance, Ojha et al. used EMG signals acquired from the lumbar erector spinae muscle group to evaluate muscle activity while using exoskeletons. The research leveraged various time and frequency domain features including mean absolute value (MAV), root mean square (RMS), mean number frequency (MNF), and power spectral density (PSD) for evaluation [30]. In other work, Doerschul et al. leveraged a multivariate autoregressive model to derive functions for various forearm movements using EMG signals [31].

While promising, traditional EMG systems using clinical electrodes encounter significant challenges, particularly during dynamic tasks common in construction work. Notably, they contribute to discomfort for users during prolonged wear and exhibit poor skin contact, compromising signal quality. This lack of adequate skin contact, coupled with the vigorous and varied movements inherent to construction tasks, can lead to pronounced motion artifacts [32]. These artifacts, stemming from the sensor's inability to maintain consistent contact with the skin, pose a considerable threat to the fidelity of acquired EMG signals. Consequently, the reliability and accuracy of data captured by traditional EMG systems in such demanding environments are significantly compromised, necessitating innovative solutions to address these limitations effectively.

2.3. Wearable physiological sensing and motion artifact

Motion artifacts represent a notable challenge arising from the movement of either the sensor or the body during physical activities, leading to distortion or noise within the captured signals [33] While motion artifacts may not pose a significant issue in clinical settings, where subjects typically remain seated in a resting position with minimal movement, their impact becomes considerably pronounced in dynamic environments such as construction sites. Here, workers are engaged in diverse activities necessitating extensive movement, making them particularly susceptible to the effects of motion artifacts [33]. As a result, the accuracy and reliability of data collected in these settings are significantly compromised, highlighting the critical need for robust solutions to mitigate the impact of motion artifacts on signal quality and fidelity.

Recent works have explored several algorithmic solutions to this problem including wave techniques and machine learning-based frameworks like autoencoder [14,34,35]. These algorithms analyze the temporal and spectral characteristics of the sensor data to identify and filter out artifacts, enhancing the signal-to-noise ratio and preserving the integrity of the physiological measurements. Additionally, advancements in sensor design, such as the integration of inertial measurement units (IMUs) or gyroscopes, enable sensors to detect and compensate for motion-induced disturbances in real-time. In a recent work, Liu. et al. developed an adaptive filtering method to reduce motion artifacts in various physiological signals including PPG, ST, and EDA signals acquired in a construction setting [33]. In another work, Márquez-Figueroa et al. leveraged kalman filter-based method for reducing motion artifacts in EMG signals [36].

Despite the efficacy of algorithmic methods in enhancing signal quality and attenuating motion artifacts, they have their mathematical limitations. While they can increase the signal-to-noise ratio up to a certain threshold, they may fall short in compensating for data loss resulting from poor skin contact and high levels of motion artifacts [32]. Moreover, in scenarios where signals exhibit a very high signal-to-noise ratio, which is common in cases of poor skin contact, partial sensor attachment, and tasks involving significant movement [37], algorithmic approaches may struggle to recover the true underlying signals due to excessive noise contamination. In such scenarios, enhancing the physical process of data acquisition emerges as the most viable solution to minimize data loss and corruption. This necessitates innovative sensor design aimed at improving skin contact and resilience against motion typical of dynamic actions encountered in construction tasks. By optimizing electrode design, it may become feasible to maintain consistent skin contact and stability during movement, thereby reducing the likelihood of signal distortion and artifact generation [38].

2.4. Flexible sensor for health monitoring

Recent breakthroughs in materials science have propelled the development of flexible sensors, offering a radical shift from traditional rigid designs. Recent works have explored innovation in electrode patterns, flexible substrates, and electrode material to obtain desired flexibility and conformance to natural skin. Past studies have explored various fractal-based designs like Hilbert curve, Peano curve, and serpentine designs to increase flexibility while maintaining optimum level of strength [39].

Other advancements center on novel materials such as conductive polymers, nanomaterials, and hybrid composites [40]. Possessing unique mechanical properties, these materials can bend, stretch, and conform without compromising their electrical conductivity [39]. Flexible sensor designs, utilizing thin films, and serpentine structures, offer superior skin conformity compared to their rigid counterparts [17,19]. Previous investigations have underscored the efficacy of combining conducting materials like nanowires and nanotubes with elastomeric matrices to yield systems exhibiting minimal responses to substantial strain deformations [37,41,42]. Leveraging space-filling repetitive geometries-based fractal designs can help to maximize surface area coverage while minimizing metallic density, thus enhancing flexibility. This enhanced conformability translates directly to improved adhesion, minimizing gaps between the sensor and the skin, which are a major source of signal degradation [18]. Moreover, flexible sensors can adapt to the body's movements, thus helping reduce motion artifacts that are common in inflexible commercial [43]. While novel materials and designs have shown promise in laboratory conditions, their performance in real-world applications, particularly in harsh and dynamic environments, remains underexplored. There is also a need for more comprehensive studies combining health monitoring framework with the sensing technology to develop and evaluate an unified health monitoring systems.

2.5. Research objectives and point of departure

This research aims to address the significant limitations of traditional wearable EMG sensors for monitoring the health of construction workers. The physically demanding nature of construction work, characterized by dynamic movements, perspiration, and potential for high-pressure contact, exacerbates the shortcomings of standard commercial sensors. These issues include poor skin conformity, motion artifacts, and discomfort, all of which impede accurate signal acquisition and long-term usability.

The primary objective of this research is the development of a flexible EMG sensor integrated with a fatigue estimation framework. By utilizing fractal patterns, the design maximizes flexibility and adaptability, ensuring excellent skin conformity and minimizing motion artifacts. This focus on reducing signal noise enhances the accuracy of fatigue estimation, which is crucial for timely health interventions.

The research seeks to create a comprehensive system tailored for the construction industry by combining these advanced fractal electrodes with a robust fatigue estimation algorithm. This system emphasizes user comfort for prolonged wearability, low-noise data acquisition, and significantly improved accuracy in detecting fatigue compared to conventional EMG sensors. The ultimate goal is to develop an integrated health monitoring solution that enhances the safety and well-being of construction workers in their challenging work environments.

3. Methodology

The research aims to design flexible sensor for electromyography and evaluate their performance for the fatigue assessment of construction workers. This methodology encompasses two primary phases: Phase 1 involves the design and fabrication of fractal-based printed flexible EMG sensor, while Phase 2 focuses on employing these developed sensor for fatigue assessment as illustrated in Fig. 1. During Phase 1, silver nano ink is utilized to print electrodes onto a flexible polyimide substrate using ultrasonic printing technique. Subsequently, the printed electrodes undergo sintering. This initial phase aims to fabricate electrodes that can conform to the body's movements and maintain reliable contact with the skin during dynamic tasks. In Phase 2, the electrodes developed in the first phase are utilized to conduct electromyography measurements and assess the physical fatigue levels of various muscle groups relevant to fatigue experienced by construction workers. A vision transformer-based model is developed to access physical fatigue levels based on the acquired EMG signals using 2-dimensional spectrograms. This phase aims to demonstrate the effectiveness of the designed EMG sensor in accurately capturing muscle activity and providing insights into fatigue levels during real-world construction tasks.

3.1. Fractal/serpentine design and FEM analysis for flexibility

This subsection explores the integration of fractal-based designs into electrode fabrication processes, aimed at enhancing flexibility and skin

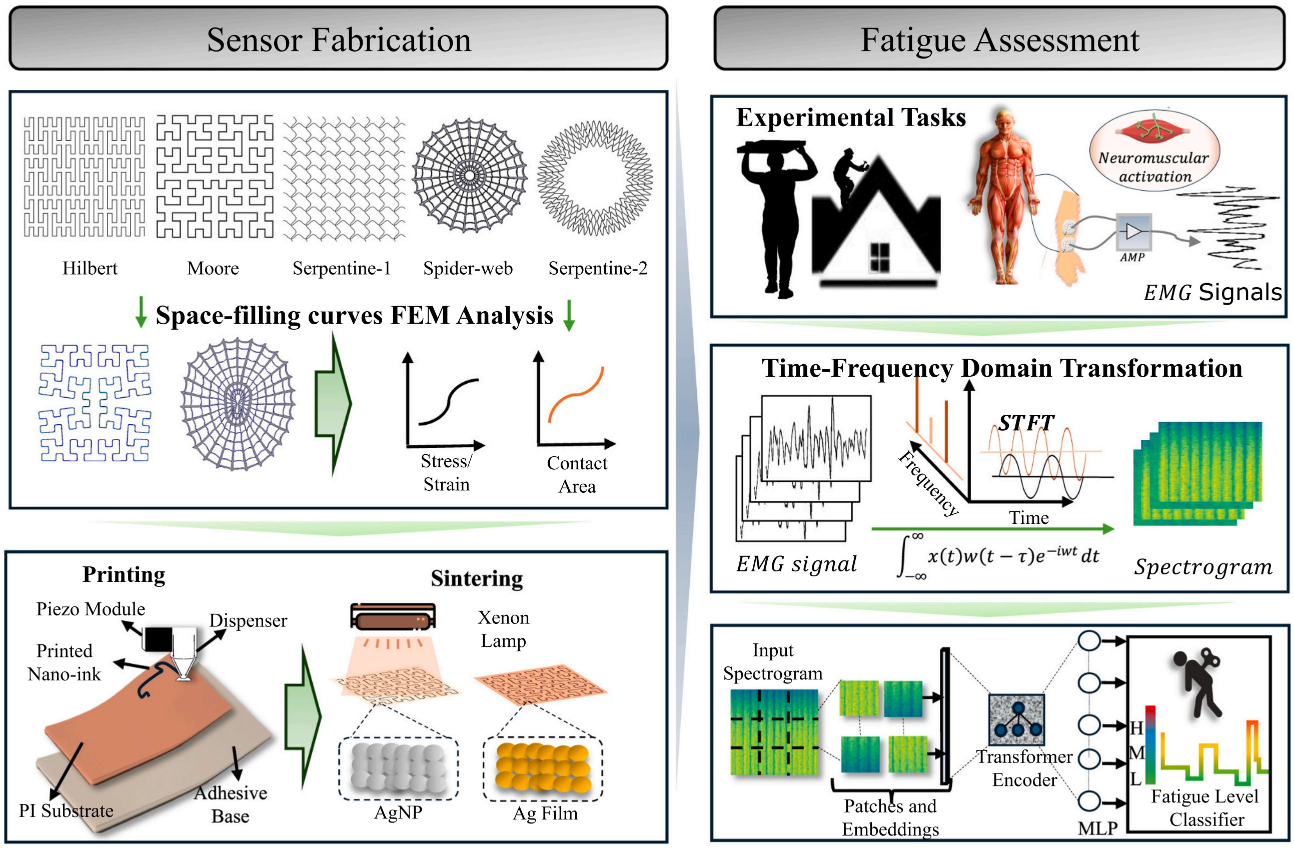


Fig. 1. Overview of the proposed methodology. The EMG sensor is fabricated in the first stage whereas fatigue assessment is performed in the second stage using a vision transformer model.

conformability for wearable physiological sensing applications. Fractal design harnesses the power of fractal geometries, such as Hilbert curves, within electrode structures. These geometries, reminiscent of patterns observed in natural systems, have been successfully utilized in developing stretchable electronics [39]. Fractal-based structures exhibit self-similarity, where subdivision into smaller sections yields pieces resembling the whole. Engineered to accommodate enhanced elastic strain along specific dimensions, these designs support various deformation modes, including biaxial and radial deformations. Moreover, the diverse range of topologies available, from lines to loops, allows for tailored applications by integrating multiple structures. Consequently, these intricate patterns enable electrodes to conform more intricately to the irregular contours of the human body, thereby mitigating contact impedance and amplifying signal fidelity.

Based on previous studies, fractal curves along with normal geometric patterns and natural patterns were designed and evaluated which included hilbert curve, moore curve, spider web design, and serpentine design-based electrodes [19,39] as illustrated in Fig. 2. The mathematical formulations for fractal curves and natural designs are presented in [44]. Hilbert and moore curve follow square guidelines to fill in the vacant space, spider web mimics pattern of spider web whereas serpentine curves are winding patterns. In this study, serpentine-1 curve has such winding patterns repeated across length and width whereas serpentine-2 has winding pattern along the circumference of a circle.

Five designs, including Hilbert, Moore, and serpentine curves of varying orders, were subjected to mechanical analysis using the Finite Element Method (FEM). This analysis aimed to assess their stretchability and stress resistance under various loading conditions. Static analysis was performed for axial loading, simulating stress and strain levels typical of those experienced by the skin, presented in detail in section 5.1.

3.2. Flexible sensor fabrication

Based on the geometric and FEM analysis presented in section 5.1 serpentine-1 curve was printed in a flexible polyimide substrate using fluid injection based on ultrasonic pumping. Ag nano ink was used as the electrode material with polyimide substrate.

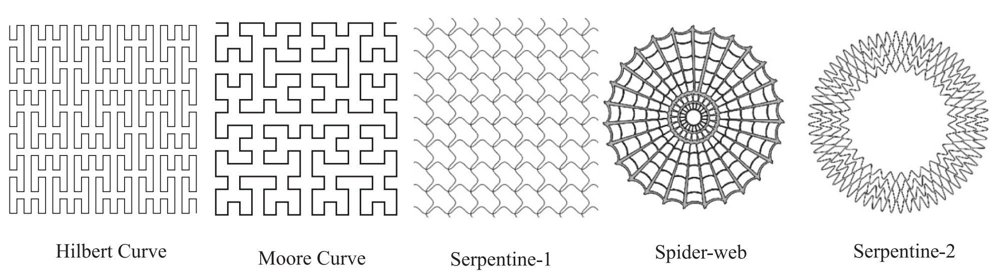


Fig. 2. Space-filling geometries analyzed for the development of the EMG sensor. The FEM results are presented in section 6.1.

3.2.1. Direct ink writing using ultrasonic printing mechanism

The designed EMG electrodes are fabricated using a commercial DIW machine, SonoPlot® Microplotter proto. The ultrasonic printing mechanism is based on a specified high-frequency vibration of the dispenser where the pumping and spraying action of the nano inks occurs. The dispenser consists of a hollow glass tapered structure to hold the nanoink material which is then attached to a piezoelectric element. The vibrating frequency of the piezoelectric component is controlled through alternating current as given by $V(t) = V_0\, sin(\omega t)$, where $V(t)$ represents the voltage applied to the piezoelectric element as a function of time t, V_0 denotes the maximum voltage amplitude, and ω represents the angular frequency of the alternating current (AC), given by $\omega = 2\pi f\omega = 2\pi f$, where $f$is the frequency of the AC signal. The frequency of the input AC is controlled through the computer system for vibrating the dispenser to the desired level. The instrument uses integrated camera control for a precise computer-controlled fluid dispensing assembly.

3.2.2. Nano ink and substrate description

The choice of electrode material requires a balance between conductivity, flexibility, and the ability to provide ultrasonic printing. Viscosity, surface tension, and the particle size of ink can influence the printing results. Higher viscosity may cause higher flow friction for the nano ink material and thus prevent smooth spraying. Lower surface tension facilitates surface adherence to the substrate whereas small particle size can support smooth patterning. The physical characteristics of the nano-ink and the substrate material is tabulated in Tables 1 and 2 respectively.

The substrate provides physical support for the electrode pattern thus helping enhance flexibility as well as acceptable yielding strength to the designed electrode. On the other hand, it should also act as an insulator to block the electrical connection between electrodes and the outer environment. Polyimide Kapton HN Film 0.125 mm (Sigma Aldrich) was selected because of high flexibility, low density (lightweight), higher elongation, and low thermal expansion.

After printing, the obtained samples are not conductive because the solvent does not evaporate and the AgNPs are not sintered. A benchtop Pulsed Light system (X-1100 from XENON Corporation) was used to sinter the AgNPs. For nano inks, pulsed light sintering offers a rapid and low-heat alternative to traditional sintering methods, which can damage delicate and thin substrate material.

3.3. Physical fatigue estimation

After acquiring the required EMG signals from the developed sensors (explained in detail in Section 4) and following corresponding signal processing, including labeling and windowing, the resulting dataset is leveraged to train the proposed machine learning framework. For labels, Borg Fatigue rating is used as described in section 4.

The proposed methodology leverages short-time Fourier Transform (STFT) to convert the time-domain EMG waveforms into 2D spectrograms. STFT can be defined by Eq. 1. The function operates through a sliding window (ω) transforms the time-domain signal into a frequency-time graph.

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

Table 1
Description of the Ag Nanoink.

Description	Quantity
Composition of AgNP	50 % weight
Solvent	Tripropylene glycol mono methyl ether
Resistance (aftetr sintering)	≤20 μΩ-cm
AgNP Diameter	115–70 nm
Surface Tension	24 dyn/cm
Viscosity	24 cP

Table 2
Description of the Polyimide Kapton HN Film 0.125 mm.

Description	Quantity
Density (g cm^{-3})	1.420 g
Coeff of thermal Expansion (x10^{-6} K^{-1})	30.000–60.000
Thermal Conductivity (W m^{-1} K^{-1})	0.1–0.35
Tensile Strength	70–150 MPa
Tensile Modulus	2–3 GPa

Here, x represents raw EMG signals in the time domain whereas $w(t)$ represents a non-zero window function.

The generated spectrogram is then used as a 2D image for input to a Vision Transformer (ViT) model for classifying fatigue levels as depricted in Fig. 3. While previous studies have investigated manual features from spectrograms, we propose a neural network based model that has demonstrated high efficiency for similar 2D spectrograms for similar signals like speech, music, and seismic waves [45,46].

ViT is a pre-trained model trained on Imagenet-21 K which is a large dataset comprising of 14 million images along with 21,843 classes. This is based on work presented in [47]. The Vision Transformer leverage self-attention mechanisms to process entire images as sequences of tokens. This architecture is defined by its ability to capture long-range dependencies and global context, essential for understanding complex spatial relationships in images. The ViT model consists of multiple Transformer blocks, each comprising self-attention and feedforward layers. The self-attention mechanism in ViT can be mathematically expressed as follows:

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

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. This equation computes weighted sums of the values V based on the similarity (scaled dot-product) between queries Q and keys K. In practice, ViT transforms an input image into a sequence of tokens, each representing a spatial region of the image. These tokens are processed through multiple Transformer blocks, wherein each block refines the token embeddings by attending to different parts of the input sequence. The Vision Transformer (ViT) architecture incorporates feedforward neural networks within each Transformer block to further process token embeddings. This process can be represented as in Eq. 3.

$$FFN(x) = ReLU(xW_1 + b_1)W_2 + b_2 \tag{3}$$

where x is the input token embedding, W_1, b_1 are weights and biases of the first linear layer, and W_2, b_2 are weights and biases of the second linear layer. The ReLU activation function introduces non-linearity, enhancing the model's capacity to capture complex patterns within token sequences.

In the context of retraining ViT for fatigue level classification from EMG spectrograms, the model's parameters W_1, b_1, W_2, b_2 are adjusted during fine-tuning. This adjustment process optimizes the ViT's ability to extract and integrate hierarchical features from spectrogram tokens, crucial for accurate classification. When applied to EMG spectrograms for fatigue level classification, the ViT's pre-trained weights are fine-tuned on a specialized dataset. This adaptation process adjusts the model's parameters to the unique muscle activity patterns encoded in the spectrograms.

$$H\left(g_f(I_{2D})\right) = -\sum_{j=1}^{k} y_j log\left(g_f(I_{2D})\right) \tag{4}$$

For training the model categorical cross entropy is used as a loss function (Eq. 4) with classification accuracy as the main metric. 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

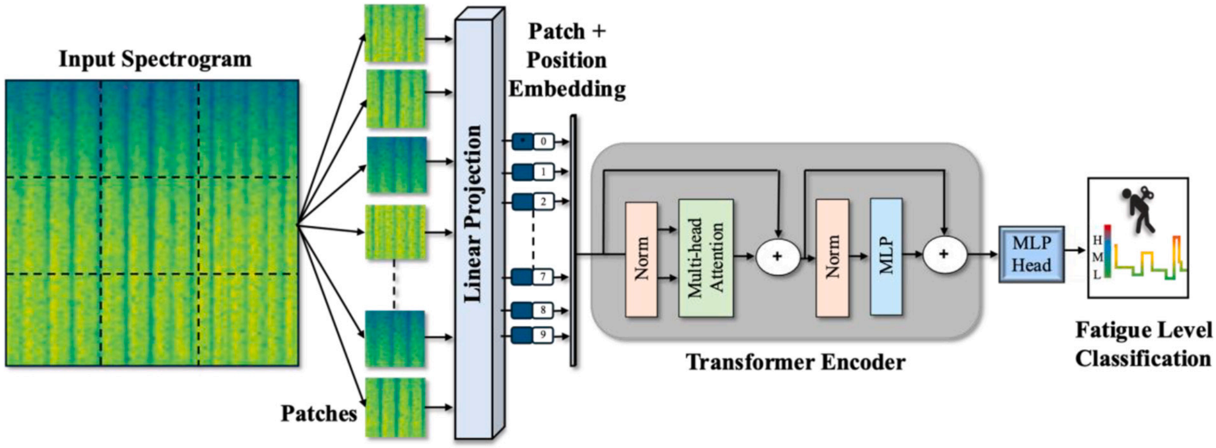


Fig. 3. Vision Transformer model-based fatigue detection framework using EMG spectrogram as input and classifying fatigue states of low, medium, and high.

classes. This loss function guides the ViT to accurately predict fatigue levels based on learned features extracted from EMG spectrograms. During training, the model's parameters are optimized using the Adam optimizer with a learning rate of 5e-5, minimizing the categorical cross-entropy loss function to enhance classification accuracy. By adapting the ViT's learned representations to the specifics of EMG spectrogram features, we aim to achieve robust performance in accurately predicting fatigue levels, demonstrating the model's adaptability and effectiveness in biomedical signal analysis.

4. Experimental scheme

To evaluate the performance of the developed sensor model and compare it with the commercially available electrodes, 12 volunteers were recruited for the study, where the subjects performed controlled material handling tasks and roofing tasks typical of a construction environment. Within-subject design was used to acquire and compare the performance of the designed and commercial electrodes. Roofing task involved hammering shingles onto a roof frame angled horizontally, while the materials-handling tasks involved lifting material loads of variable weights. The study was performed in accordance with IRB protocol- 24,141 approved by the Office for Protection of Research Subjects, UIUC. Before the experiments, the authors confirmed that subjects had no history of any medical condition that could affect their performance in the experimental tasks. Then the subjects were informed about the procedure and consent was obtained. After that height and weight were measured for every subject. EMG signals were acquired through the developed electrodes as well as commercial electrodes. The acquisition frequency for the EMG signals was 1 KHz.

4.1. Instruments and muscle groups

A four-channel amplifier (ADInstruments) was leveraged to acquire the signals from the subjects. For this study, three sets of muscles including biceps branchii, brachioradialis, and gastrocnemius were used for recording the EMG signals as presented in Fig. 4.

As the tasks were designed to focus on different muscle groups, two sets of datasets Dataset 1 and Dataset 2 were classified based on the experimental tasks and the muscle group of interest. Dataset 1 comprises of roofing task during which EMG signals were acquired from biceps brachii and brachioradialis. Dataset 2 comprised of material handling tasks and had EMG signal acquired from Gastrocnemius. The distinction and differentiation of the two datasets are further elaborated in the next subsection.

4.2. Data acquisition and labeling

To label the acquired EMG signals with the fatigue scale, Borg's Rating of Perceived Exertion (RPE) was leveraged based on previous investigations [29]. Verbal feedback was used at an interval of an average of 5 repetitions with an average interval of 20 s and comprised of a single instance of a sample. A window size of 3 s was used to capture a single instance of feature and a stride of 1 s was used along this sample space. In total 12 subjects were employed for the study making it 24 total sets of data for the 2 tasks. For all the cases, the pair electrodes were placed longitudinally across the respective muscle group. The labels had

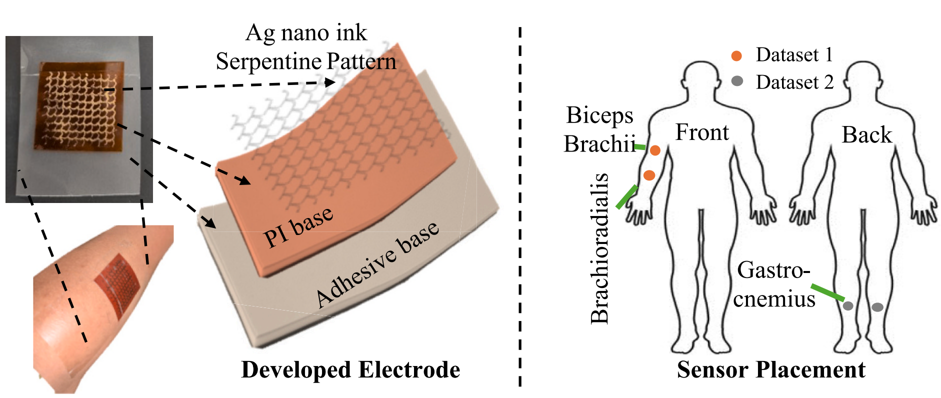


Fig. 4. Electromyography signals acquisition framework: (left) Developed electrode design along with the alligator clip connection; (right) Sensor placement location for various muscle groups.

three classifications high, medium, and low based on the RPE.

Dataset 1 comprises experiments involving roofing tasks, specifically hammering. The task was chosen because of its commonality in construction, and strenuous nature. The hammering task required participants to hammer nails into an experimental roofing structure for 70 sets where each set consists of 5 hits. The first 35 sets were performed using a lighter hammer of 10 oz. whereas the last 35 sets were performed using 16 oz. hammer. This was done to deliberately induce higher fatigue in later stage compounded with the effects of previous work and higher load. During this experiment, EMG signals were acquired for the biceps and brachioradialis muscles. To prevent any trial effects or selection bias, half of the participants began with the material handling task, while the other half started with the roofing task. Between these two tasks, 30 min of mandatory and rehydrating breaks were provided.

Dataset 2 comprises experiments focused on material handling. In this experiment, workers lift materials from the ground to a height of 90 cm, as shown in Fig. 5. The process involves lifting the material from the ground, placing it back down, and repeating this action to complete a single round of trials. Verbal feedback is recorded after every 5 repetitions/trials which comprises 1 set. The first 7 sets are done without any weight to set up the subject as well as to induce low fatigue situations. The following 7 sets are done at a weight of 5 lbs. so as to induce incremental fatigue. The last 7 sets are done with a load of 30 lbs. so as to induce effects of high weight and long time for inducing high fatigue. Each subject performs a total of 105 repetitions which has an average time of 24 min. The subjects can take momentary breaks at their discretion or halt the experiment if they feel too tired. Two subjects did not complete all 105 trials.

A separate set of experiments was performed to assess the precision and sensitivity of the developed electrodes for which subjects performed wrist flexion, clenching, wrist extension, and ankle extension/flexion. This was done at the very beginning, before the experimental construction tasks so the subjects did not have any effects of fatigue.

4.3. Finite element analysis

The fractal curves were subjected to finite element analysis (FEA) prior to fabrication to assess their mechanical properties.

Model Preparation: The fractal curve designs were 3D-modeled using solid modeling techniques in FreeCAD. This approach ensured that the models represented solid structures, necessary for accurately simulating mechanical behavior during analysis. Material Properties: The modeled sensors were assigned material properties characteristic of pure silver, known for its linear elastic and isotropic nature. The material was defined with an elastic modulus of $7.1 \times 10^{10}\ N/m^2$, tensile strength of $1.25 \times 10^8\ N/m^2$ a Poisson's ratio of 0.37, and a density of $11,000\ kg/m^3$. Boundary Conditions: To simulate realistic stretching conditions, fixed supports were applied along one edge of the model, representing attachment points during use. An axial force was applied along the opposite edge to replicate the stretching action. Meshing Strategy: A curvature-based meshing approach was employed to balance computational efficiency with the precision of the results. This technique facilitated an even distribution of elements across complex geometries, ensuring reliable stress and strain distribution analysis. Analysis Process: Static analysis was performed under controlled axial loading conditions. Considering previous research indicating that typical skin-stretching forces range from 0.5 N to 2 N [50], the model was subjected to an axial load of 1 N (approximately 100 g). This force was applied uniformly along the edge opposite to the fixed support to evaluate stress and strain distributions effectively. The analysis focused on extracting critical strain values, with detailed findings provided in section 5.1.

5. Results

The designed electrode has been accessed through multiple evaluations, including its performance for motion artifact reduction, muscle activity response, local fatigue estimation, and precision. The results are presented in the following subsections:

5.1. Finite element results for various designs

Five different designs including fractal curves, spider webs, and serpentine design patterns were initially analyzed geometrically and through the finite element method to evaluate the flexibility and contact area as presented in Fig. 6. Previous investigations have shown grip force during normal skin stretching can be in the range of 0.5 N to 2 N [48], thus the analysis was performed using an axial loading of 1 N (100 g).

Upon evaluation, the serpentine-1 curve had the highest area coverage whereas the spider-web pattern exhibited higher flexibility with the lowest equivalent strains. Linear area has been used as the length of the pattern as the patterns are printed with constant thickness. Hilbert and moore curves both had significantly lower linear area and

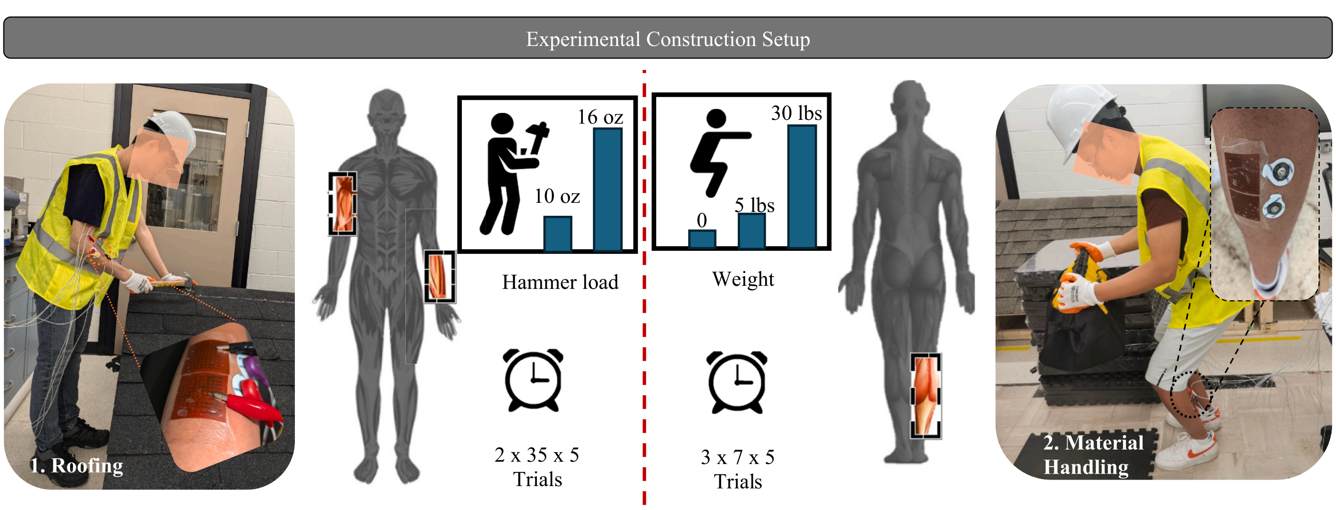


Fig. 5. Experimental setup for the construction tasks. Task 1 comprises roofing where the subject hammered nails into singles and roof frame (Dataset 1) and EMG signals are acquired from the biceps and forearm muscle group with corresponding wired connection. Task 2 comprises of material handling task where the subjects lift varying loads to a height of 90 cm in a squat posture and EMG signals are acquired from the gastrocnemius muscle group with sensor placement location.

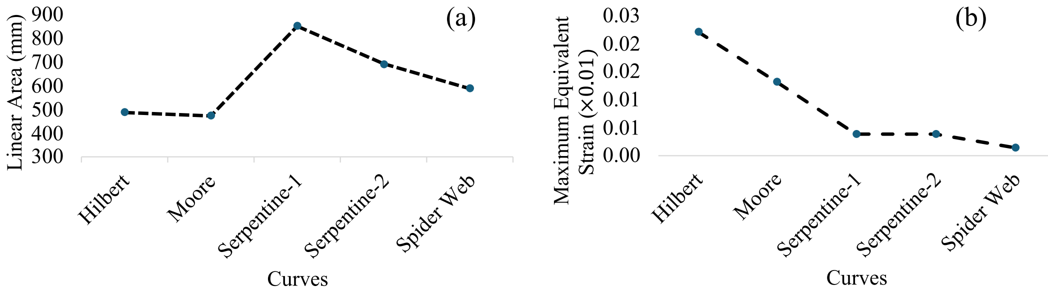


Fig. 6. Finite element Analysis for the various designs including (a) Linear Area (b) Maximum Equivalent Strain under an axial stretching of 1 N.

high strain and local displacement. The strains were typically high in planes with low continuity as in Hilbert and moore curves. On the other hand, the circular pattern for serpentine and spider web-based design provided a nearly constant continuous segment. This also causes nearly isotropic property of flexibility for these circular patterns whereas the flexibility pattern can be anisotropic for the square-based space-filling curves like Hilbert and moore as the pattern connectivity can vary across different planes. Based on these results, the serpentine curve-1 was chosen for printing purpose as it has the highest contact area along with the lowest equivalent strain.

5.2. Reduction in motion artifact

After fabricating the sensor, its efficiency in reducing motion artifacts was evaluated by measuring the signal-to-noise ratio (SNR) [43] of the EMG signals it acquired. These SNR values were then compared to those obtained from commercial sensors. For each muscle group in both data sets, the average SNR values of MA-contaminated EMG signals are listed in Table 3. These values served as a comparison metric for evaluating the performance of the developed electrodes in removing artifacts from the signals.

For the biceps muscle (Biceps Brachii), the developed electrode has a SNR of 18.5. The baseline value recorded for the commercial electrode was 13.5, showing a 37 % improvement. For the forearm muscle (Brachioradialis), the SNR for the developed electrode was 13.5, compared to the baseline value of 8.5 for the commercial electrode, indicating a 59 % improvement. For the calves muscle (Gastrocnemius), the developed electrode achieved an SNR of 20, while the commercial electrode had a baseline value of 17.5, resulting in a 14 % improvement. As expected dataset 1 has lower SNR as it involves very heavy motion of the forearms and biceps during hammering. These SNR comparisons between the MA-contaminated EMG signals) clearly demonstrate that the developed electrodes significantly reduce motion artifacts compared to commercial electrodes.

Fig. 7 presents the performance of the developed and commercial EMG electrode for the construction tasks as defined in section 4 along with subject-wise variation of average SNR values. For simplicity, Fig. 7 reports the average SNR for signals acquired from each electrode in each data set. The average SNR was determined as the mean value of the SNR for all subjects in the data set.

Table 3
SNR comparison of developed and commercial electrodes for MA-contaminated signals for different muscle groups.

S. no	Muscle Group	Designed electrode	Commercial Electrode	% improvement
			SNR	
1	Biceps (Biceps Brachii)	18.5	13.5	37 %
2	Forearm (Brachioradialis)	13.5	8.5	59 %
3	Calves (Gastrocnemius)	20	17.5	14 %

5.3. Fatigue assessment for various muscle groups

A fatigue estimation model based on a transformer network was developed. It was then leveraged to evaluate and compare the performance of the developed electrode with that of the commercial electrode. The EMG signals for different muscle groups, including bicep muscles (bicep brachii), forearm muscles (brachioradialis), and calves (Gastrocnemius) were acquired and models were trained for fatigue assessment. The comparison results are presented in Fig. 8 with overall accuracy and recall value for high fatigue. As an accurate classification of high fatigue would be more important for the safety of construction workers these metrics have been used for comparison.

On average, the developed electrode was able to increase overall accuracy by 10 % while the recall value by 9 %. Significant improvements in fatigue assessment were observed for the gastrocnemius muscle group.

As described earlier in section 3.3, a ViT model was leveraged for the fatigue assessment. The sampled spectrogram (Fig. 9) is used as input with fatigue classes as output. The detailed analysis can be observed through the confusion matrix as presented in Fig. 10.

The fatigue assessment results from EMG signals reveal significant differences in performance between the developed and commercial electrodes. For low fatigue levels, the developed electrode correctly identified 89.11 % of cases, compared to 83.33 % for the commercial electrode, demonstrating superior accuracy. In the medium fatigue category, the developed electrode achieved an 85.11 % accuracy, substantially higher than the 72.73 % recorded for the commercial electrode. For high fatigue levels, the developed electrode showed an impressive 86.02 % accuracy, outperforming the 80.65 % accuracy of the commercial electrode. These results indicate that the developed electrode not only improves signal quality but also enhances the reliability of fatigue assessment across different levels of muscle fatigue, making it a valuable tool for more accurate and consistent EMG signal analysis in construction settings.

5.4. Precision and resolution

Precision and resolution metrics were evaluated to gauge the sensor's ability to accurately capture subtle changes in muscle activity associated with physical movement. This characteristic of the electrode is important to evaluate the responsiveness and sensitivity of the developed electrode. For this study, small wrist movements were used to evaluate a range of responsiveness. These metrics provide insights into the sensor's reliability and sensitivity in detecting fatigue-related signals for varying muscle groups which can have significant differences in corresponding electrical signals.

The sensor's response to small muscular motions, such as those involved in the movement of the wrist and feet, was examined to assess the sensor resolution and precision. EMG signals were acquired from gastrocnemius, and brachioradialis for the ankle and wrist movement respectively. The individual results are presented in Fig. 11.

The sensitivity for clenching, wrist extension, wrist flexion, and

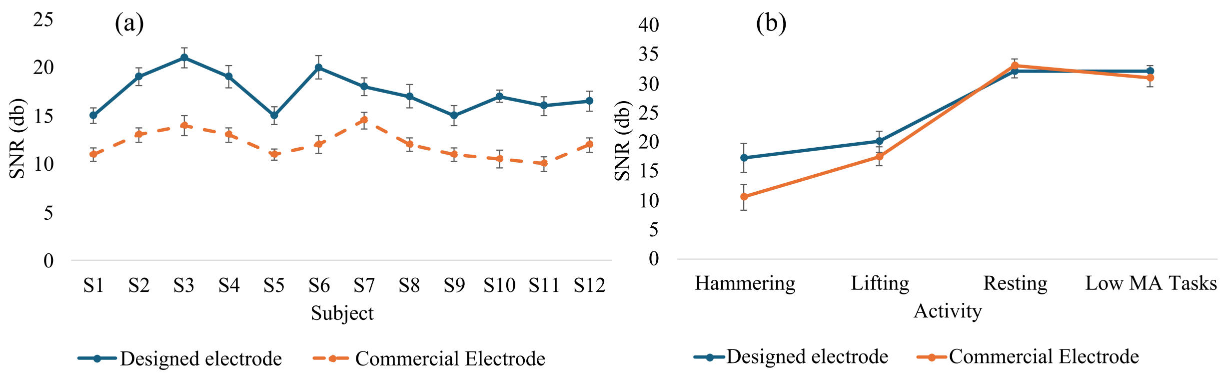


Fig. 7. Variation observed in the SNR values for the developed and commercial electrode (a) Subjectwise Variation (b) Activitywise Variation.

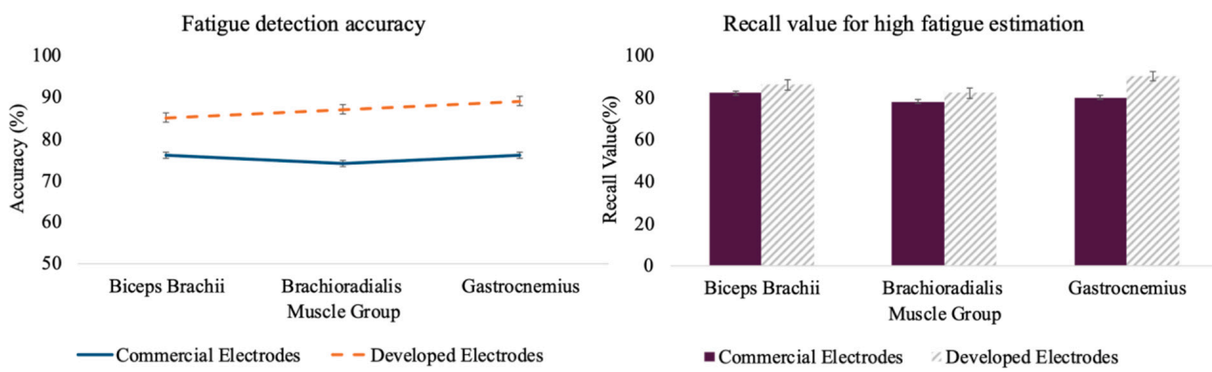


Fig. 8. Fatigue assessment comparison for the developed electrode with the commercial electrode in terms of overall accuracy and high fatigue recall value.

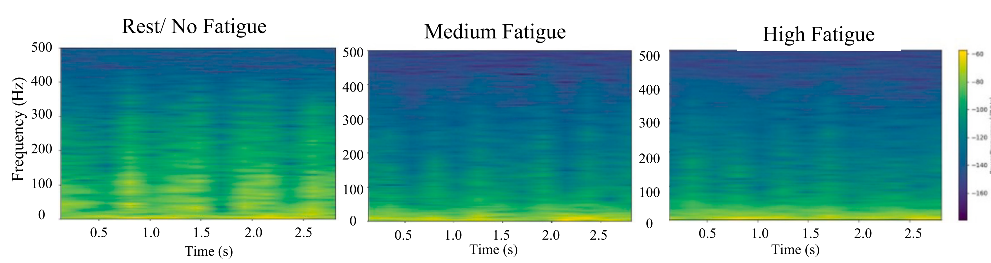
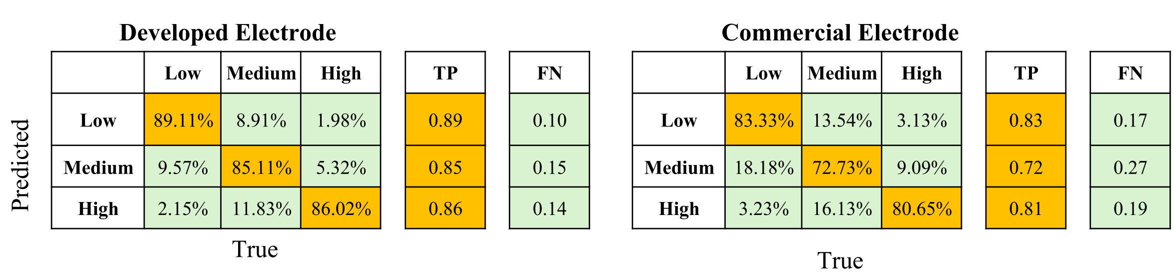


Fig. 9. Spectrogram sample for EMG signals acquired from gastrocnemius muscle during low, medium, and high fatigue states.



Developed Electrode (Predicted vs. True)

	Low	Medium	High	TP	FN
Low	89.11%	8.91%	1.98%	0.89	0.10
Medium	9.57%	85.11%	5.32%	0.85	0.15
High	2.15%	11.83%	86.02%	0.86	0.14

Commercial Electrode (Predicted vs. True)

	Low	Medium	High	TP	FN
Low	83.33%	13.54%	3.13%	0.83	0.17
Medium	18.18%	72.73%	9.09%	0.72	0.27
High	3.23%	16.13%	80.65%	0.81	0.19

Fig. 10. Confusion matrix for the fatigue assessment for the developed and commercial electrodes with values for True Positive and False Negative.

ankle was calculated to be 0.003, 0.0019, 0.01, and 0.007 mV/degree respectively. For wrist flexion and extension, EMG signals were acquired from the brachioradialis muscle group whereas for ankle flexion/ extension, EMG signals were acquired from the gastrocnemius muscle.

6. Discussion

The developed fractal-based electrode demonstrated high feasibility in reducing motion artifacts and providing signal acquisition with high accuracy, precision, and sensitivity. Specifically, for Dataset 1, the developed sensor platform was able to improve the SNR by upto 59 % compared with the commercially available sensors; for Dataset 2, using the same electrode, the SNR value improved by up to 14 %. The designed electrode had the optimal performance in rejecting motion artifacts. Moreover, the developed sensor was able to provide 12 % improved overall accuracy for the fatigue assessment there was 13 % reduction in

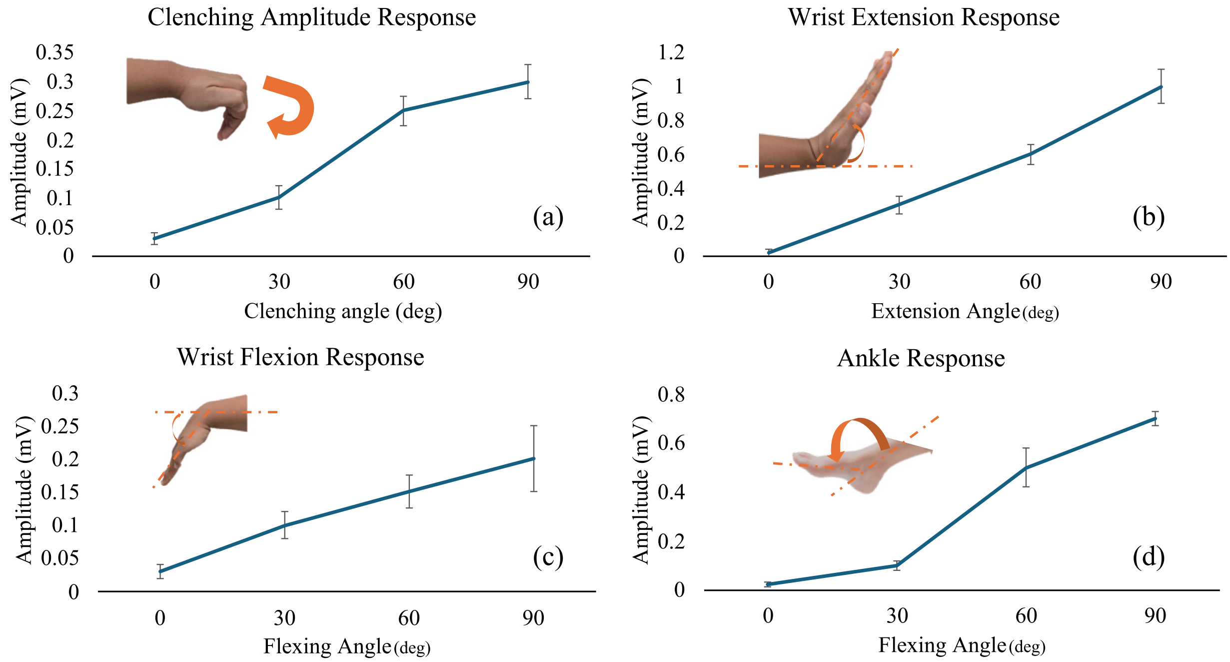


Fig. 11. Amplitude response for various small motions of wrist and ankles: (a) Clenching amplitude response; (b) Wrist extension response; (c) Wrist flexion response; (d) Ankle extension response.

the False Negative rate. The results of these comparisons reveal that the designed electrode was able to reduce motion artifacts while performing better than the commercially available electrodes.

The authors also evaluated other performance metrics including precision, and sensitivity, to further investigate its efficiency for robust acquisition of EMG signals from the developed electrodes. The developed sensor was able to detect changes in signal for up to 7 degrees for ankles while for the wrist, this was 15 degrees. The sensitivity for clenching, wrist extension, wrist flexion, and ankle was calculated to be 0.003, 0.0019, 0.01, and 0.007 mV/degree respectively.

Construction tasks are complex and involve multiple muscle groups with varying responses depending on anatomy and action pursued by the subject. For instance, one person may be using more back muscle during lifting with a bent spine whereas another subject with a better posture may engage more of hamstrings and core. To access the response variability for subjects with simpler task of wrist flexion was used before the beginning of the experimental construction tasks. Wrist flexion was performed for the right hand following a metronome beat of 60 bpm. The angle of flexion was also limited to 60 degrees. The amplitude response is presented in Fig. 12. The results demonstrated around 15 % variation among subjects for amplitude response for performing the same muscular motion at the equal speed.

External factors such as sunscreen, body lotion, and sweat can introduce variability in skin characteristics, potentially affecting the performance of wearable electrodes. A separate analysis was performed to assess the performance of the developed electrode for sweaty conditions. EMG signals were acquired for brachioradialis during wrist flexion for two conditions one initially with no sweat, one after externally hydrating the skin with wet tissue to mimic skin sweating. Wrist flexion was performed using a metronome at 60 beats per minute. The data was acquired during the beginning of the session before the experimental tasks when the subject had no physical exertion and sweating. The comparison of the SNR values in these conditions along with the sample of the output EMG signal and the amplitude-based response is presented in Fig. 10(b).

The study also evaluated the long-term use of the developed EMG sensor and compared it with the commercial one. For this EMG signals acquired from the muscle group during wrist flexion were studied for a period of 4 days (8 use cases at 12 h intervals). The response curve is presented in Fig. 13. While the commercial electrode had a 50 % lower response by the end of the fourth use case, the developed electrode had a 70 % of response for the eighth use case. The higher deterioration rate for the commercial electrode could be attributed to the use of hydrogel which had partially dried up by the third day of usage. However, as the developed sensor does not depend on any liquid for conduction, its results have not been much affected.

According to the above discussion, the developed fractal-based thin flexible EMG sensor has the potential to promote more efficient EMG-based health monitoring in the construction industry for construction workers. The designed sensor enable a more reliable usage of electromyography signals for various types of muscular monitoring of construction workers including movements and muscular fatigue. Furthermore, the framework can be integrated into algorithms for detecting various muscular problems like fatigue, strain, etc. This can lead to improved health and quality of life for construction workers, which in turn may also increase overall productivity in construction.

Future research should focus on addressing the various limitations that are still present in this study. Firstly, the wired connection from the amplifier restricts a wide range of motion which may not be feasible for real-world construction activity. Further development may be necessary for miniaturizing the amplifying circuitry and providing it with a

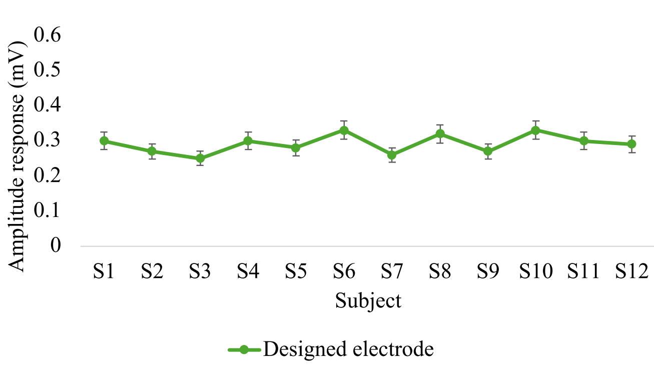


Fig. 12. Subjectwise Variation for amplitude reponse for wrist flexion.

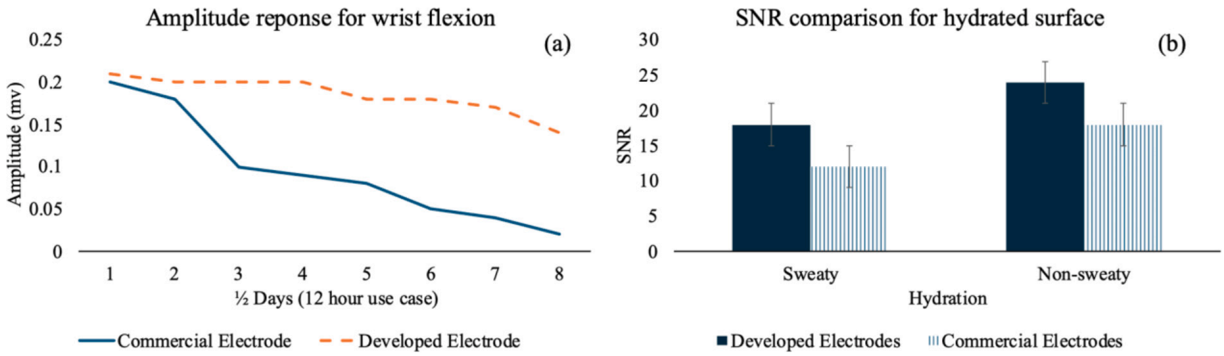


Fig. 13. Change in sensor response during skin hydration and long-term use. (a) Performance of wearable electrodes after storage for across 4 days. (b) As sweating occurs, the SNR value reduces.

flexible form as the electrodes. Also, development may be necessary to integrate NFC communication devices like Bluetooth into the module so computations and assessments can be done remotely thus enabling single-stand flexible EMG sensors. Other forms of thin electrode printing like lithography can be further explored in future investigations which can more readily support mass manufacturing. Future studies may also want to explore surface enhancement methods to ensure the conductor surface retains its conductivity over a long time. While development in sensors can remove physical constraints for reliability like low noise and high precision other factors like distribution shift may require algorithmic solutions. Future studies can also explore algorithmic solutions to reduce such distributional shifts. The work has been evaluated for only a single physiological signal (EMG), future work can explore similar sensors including ECG and EDA. Moreover, the system can be further advanced into wireless forms for scalable usage in real construction sites.

7. Conclusion

The study develops a thin flexible sensor for electromyography. In this study, the authors developed a printed electrode based on silver nanoparticle ink in a flexible polyimide substrate for providing a higher contact surface and increased flexibility to reduce motion artifacts while acquiring EMG signals during various experimental construction tasks. The results indicated the developed electrode was able to reduce motion artifact by upto 59 % with an average improvement of 42 % when compared to commercially available electrodes. The developed sensing platform was further extended to estimate fatigue levels in construction workers through a vision transformer-based model. Local fatigue assessments were performed for three muscle groups including biceps brachii, brachioradialis, and gastrocnemius. The developed transformer model was able to predict fatigue levels with an average accuracy of 87 %.

This study contributes to the field by introducing a comprehensive approach to EMG sensor design, leveraging fractal patterns and ultrasonic printing to enhance flexibility, conformity, and user comfort. These advancements address key limitations of traditional rigid sensors, making them highly suitable for the dynamic and demanding conditions of construction work. The potential impact is improved signal quality and more reliable physiological monitoring in construction settings.

The study has its limitations with portability and real-life deployment as wired connections were used for amplifying circuits which may not be feasible in an actual work environment. In this regard, future studies could work on integrating flexible amplifying circuits along with power sources and communication networks. Another limitation of the current work lies in property degradation over time, surface chemistry may be further explored to enhance properties as well as retain the characteristic for longer time. Future research could explore the efficacy of the designed methodology for analogous physiological signals from sources like ECG, EDA, and EEG, which have been utilized in construction health monitoring literature. This could help broaden the scope of applicability of the developed sensor.

CRediT authorship contribution statement

Yogesh Gautam: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Houtan Jebelli:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Houtan Jebelli reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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