International Journal of Engineering Works
https://www.ijew.io/
ISSN-p: 2521-2419
ISSN-e: 2409-2770
Vol. 10, Issue 02, PP. 01-09, February 2023
https://doi.org/10.34259/ijew.23.10020109

Workers Ergonomics Measures Enhancement Through Surface Electromyography (EMG)

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Received: 24 January, Revised: 05 February, Accepted: 17 February

Abstract— Poor ergonomics directly affect the performance of workers and its major cause is muscle fatigue. Conventional methods of fatigue assessment are unrealistic and based on the perception of an individual. Fatigue monitoring systems currently available are highly sophisticated and cumbersome to implement. There is a need for a smart real-time fatigue monitoring system. This study aims to propose an EMG-based fatigue monitoring system by targeting the bicep muscle of workers through real-time fatigue monitoring. EMG signal classifier is developed for data acquisition, manipulation, and analysis to assess muscle fatigue. In the end, a case study of gym-goers was investigated by implementing the developed system to differentiate between fatigued and non-fatigued muscles. The participants involved with poor ergonomics experienced muscle fatigue earlier than others. The proposed system can be utilized to design work-rest schedules, prevent musculoskeletal disorders, and increase the performance of employees.

Keywords— Ergonomics, Electromyography, Fatigue Analysis, EMG signal classifier.

I. INTRODUCTION

Employee performance is a term about the productivity of an employee and is pertinent to work-related ergonomics[1]. Ergonomics is the study of people's efficiency in their interaction between themselves and the working environment and the elements that are involved in the interaction. Its objective is to enhance the performance of a system by improving the interaction of people with the machine/tool. There are numerous ways to improve the system such as adjusting the task, improving the work interface and environment, and introducing more organized workplaces. The achieve the goal to implement ergonomics in an organizational system or workplace for the prevention of musculoskeletal disorders, certain harmful and undesirable factors should be eliminated such as fatigue, inefficiencies, user discomfort, musculoskeletal risks, low morale, etc. Poor ergonomic workplaces lead to musculoskeletal risks, poor quality of work, injuries, and high levels of human error, which are considered a system problem in ergonomics rather than a people problem[2]. Even after the implementation of ergonomics, some people will still experience fatigue because, for physically demanding tasks, fatigue experienced by a muscle is not by external load but generated by the muscles themselves. Every person adopts different strategies and uses different muscle patterns even when performing an identical task. This is where electromyography (EMG) plays an important part in accessing the muscle activity of workers moved in a different way to accomplish an identical job[3].

Fatigue in general is an overexertion of a muscle to a limit that results in depression of working capacity. There are two types of fatigue, mental fatigue, and physical fatigue. Physical Fatigue can be easily identified in contrast to mental fatigue. Mental fatigue is a consequence of prolonged cognitive activity which impairs cognitive ability, while physical fatigue is a result of the prolonged activity of physically demanding tasks. Fatigue is a primary cause that prompts workers to elevated error rates and perilous activities which thus adversely influences their response time, sharpness, and mental tasks related to muscle effort. Till-date various performance and muscle fatigue assessment methods have been developed like questionnaires, interviews, watching workers perform, and physiological and biochemical methods, but mostly these methods are associated with an experimental error. Therefore, the electromyogram signal is the dominant technique for fatigue estimation and ergonomic evaluation [4].

Surface Electromyography (EMG) is a technique in which adhesive electrodes are placed on the skin overlying a muscle to detect the electrical activity within muscles. The activation of muscles by nerves results in changes in ion flow across muscle cell membranes, which in turn creates electrical activity which can be monitored using non-invasive EMG electrodes which are placed on the skin over the muscle of interest. The electrical activity correlates with the strength of the muscle contraction and is dependent on the number of nerve impulses that are sent to the muscle[5]. EMG (electromyography) is based on the principle that whenever a muscle contracts, a burst of electric activity is generated within the muscle which propagates through adjacent tissue and bone and can be recorded from neighboring skin areas. “As these electrodes are non-invasive, EMG is an ideal method for monitoring physiological processes without interfering with established routines and movement patterns” [6]. EMG signals have been used for stress diagnosis to identify a certain behavioral pattern in a person. It is usually represented as a function of time, defined in terms of amplitude, frequency, and phase. EMG signals can be easily monitored by just placing the electrodes on the surface of the skin, which gives us electrical pulses of the signal passed[7].

This study aims to develop an EMG-based fatigue monitoring system for the portable acquisition of EMG muscle activity data while performing variable tasks. This study also investigated the use of Python programs for the analysis of acquired EMG data. The rest of the paper is organized as follows. Section II describes the methods of fatigue measurement and illustrates an overview of EMG-based fatigue monitoring techniques. Section III explains the methodology used for experimental setups, testing strategies, and programming codes for data analysis. Section IV is about system development and result validation. Section V is about the implementation of the developed system. Section 0 describes the conclusions and recommendations for future work.

II. Background and Overview of Related Work

There is no standard method to measure fatigue. It can be assessed subjectively as well as objectively. Subjective fatigue measures include interviews, questionnaires, and observation of behavior. Objective fatigue measurement methods focus on physiological processes such as reaction time or the number of errors[8].

Fatigue perception is estimated using validated scales prompted for assessment. Self-reporting scales are widely used to access different aspects of fatigue. The majority of these scales were designed for the chronic fatigue-affected population but have been applied to the physiological fatigue-affected population as well. Examples of such scales are the Fatigue questionnaire/fatigue scale (FQ/FS), Fatigue assessment scale (FAS), Fatigue impact scale (IS), Fatigue severity scale (FSS), and visual analog scale to evaluate fatigue severity (VAS-F). The Ecological Momentary Assessment (EMA) and the experience sampling method (ESM) are techniques used for the real-time measurement of behaviors/experiences and feelings occurred during an individual's daily life routine-based settings[9].

Fatigue can be assessed by quantifying the decrease in reaction time during prolonged physical task performance or the error rate while performing the fatigue-inducing task. The direct approach to measuring fatigue is the real-time continuous measurement of fatigue during a physically demanding task. The indirect approach consists of the measurement of cognitive ability to perform a task before and after the prolonged period of task performing during which effort may vary[10]. In Cognitive assessment, fatigue leads to the decline of cognitive performance such as degradations in visual scanning, processing speed, memory, and other measures. In physical assessment, fatigue is primarily quantified as a decrement in performance, power, speed, sense of effort, or accuracy after performing a task requiring physical effort. Heart rate may depict an increasing trend or decreasing trend in response to physical fatigue or mental fatigue as measured in cardiac physiology through recorded electrocardiogram (ECG) signal. Fatigue due to sleep deprivation has been examined with the state of keeping the eyes closed or having constant changes in pupil diameter. Electrooculogram (EOG) is another method to detect fatigue which measures the electrical activity between the cornea and Bruch’s membrane. Electroencephalogram (EEG) and the evoked response potential (ERP) are the main neural electrophysiological measures to assess fatigue in the general population. Researchers have also used EEG in combination with other fatigue-measuring methods for better detection of fatigue. Biological markers for fatigue assessment including plasma glucose, cortisol, and melatonin are used for hospitalized population. Sleep and physical activity are the most common behavioral markers to detect fatigue. These markers can be measured continuously for extended durations. In most recent studies, researchers used wearable to assess sleep and physical activity through EEG, EOG, ECG, and EMG signals[9].

As a part of the physical assessment method for detecting physical performance fatigue in a dimension of muscular strength and quantification of muscle fatigue perception, the Electromyography (EMG) technique is used by measuring the electric potential of muscle. The EMG signal acquired in the clinical domain is based on invasive methods, either by inserting the needle directly into the muscle through the skin or by measuring surface EMG using wired electrodes placed on the skin. However, with recent advancements in sensing technologies, wearable and portable sensors are available, contributing to enhancing job site conditions. The electromyography signals are received through the Ag-AgCl electrodes, which are conductive materials used for gathering and transferring the muscle activation potential. In this context, wearable EMG has opened a new door toward a noninvasive and continuous measurement of a worker's muscle activity[5]. Surface electromyography (sEMG) is a very effective technique to access muscle fatigue because EMG signals give very broad information about muscle activities. The EMG signal processing methods to detect muscle fatigue during static and dynamic movement is categorized into three domains i.e. Time domain, Frequency domain, and Time-Frequency domain. The recorded EMG signal is filtered to remove noise and artifacts. Muscle fatigue can be detected by observing the amplitude of the EMG signal. The frequency of EMG signal shows a decreasing trend in case of increasing muscle fatigue. For both time and frequency domains, EMG signal attributes are related in different ways, which can be processed through combined analysis of the EMG frequency spectrum and amplitude[11]. Fatigue monitoring system efficiency based on physiological indexes like EMG is generally higher. The average power frequency of the EMG power spectrum is the characteristic value in accessing muscle fatigue. A low average power frequency of the EMG signal indicates that a muscle is fatigued[12].

Motion capture and surface EMG (sEMG) along with questionnaires were used to investigate the ergonomic risks in a banana harvesting task[13]. Upper body ergonomics of motorbike riders were studied using surface EMG to investigate the effects of different postures on the musculoskeletal system and purpose ways to reduce muscle strain and discomfort while riding a motorbike [14]. The combination of machine learning algorithms and muscle EMG data can be a very useful tool for evaluating workplaces from the perspective of ergonomics enhancement by studying a variety of movements and tasks [15]. A comparative study of musculoskeletal injury rate among gym-goers who perform weight lifting under the supervision of a trainer or without supervision, concluded that the musculoskeletal injury rate is more in unsupervised weight lifters than supervised weight lifters[16]. The use of a low-cost EMG monitoring system was empirically investigated for the classification of finger movement. EMG signals are also used in the field of Bio-robotics for gesture control applications[5]. The amplitude of the EMG signal is variable in nature and appropriate signal processing is required for interpreting and using the signal. Hassan et al.[17] introduces a non-invasive sensing technique using a one-channel sEMG to monitor and evaluate the ingestive activities to differentiate between drink, meal, and snack eating activities. Farago et al., [18] researched on high precision activity tracker based on the correlation of accelerometer and EMG data. Orguc et al., [19] presented a study for EMG-based real-time stress monitoring and classification of different facial gestures. Integrated IC and electrode sensors with FPGA device can be used to collect EMG data and data is processed in the computer using MATLAB software. Rehabilitation Support systems utilize EMG, acceleration sensor, and gyro sensor data to plan rehabilitation treatment [20]. Non-ergonomic postures in any work environment can create risks of work-related musculoskeletal disorders (WMSD). RULA is effective to identify different ergonomics postures and discomfort at all levels but is not much effective for highly dynamic movements and EMG overcomes the shortcomings of the RULA method. Muscle activity data from wearable EMG can be most effective in developing accurate muscle fatigue monitoring and ergonomics scoring system[21]. A study was conducted to perform EMG signal-based muscle fatigue assessment and monitoring for knee rehabilitation[22]. Nicholls et al., [23] developed an automatic eating behavior monitoring system through wearable electromyography (EMG) sensors. Islam et al.,[24] researched EMG-based Health Monitoring Systems. There are various fitness and health monitoring systems based on EEG monitoring and ECG monitoring, but only a few applications for EMG monitoring. Gilbert et al.,[25] performed the feasibility study to assess the ergonomic strain and positioning by implementing surface electromyography (sEMG) and RULA technique while performing bronchoscopy procedures which involve repetitive hand maneuvers for a long time. Poor ergonomic positioning will put healthcare workers at risk of work-related musculoskeletal disorders (WMSDs). Advancements in the technology of procedural tool design and techniques are associated with the improvement of work-related ergonomic measures. Sowmya et al.,[4] investigated the effectiveness of the EMG method in stress diagnosis and concluded that EMG signal is an efficient technique to diagnose stress and EMG muscle activity data can be analyzed using Neural Networks to estimate stress. Real-time fatigue monitoring through wearable EMG electrodes can be used to prevent accidents during construction work by developing an alarming system for a high level of fatigue and work-rest schedules of workers can be altered accordingly to enhance worker safety [26] and [27]. In contrast to conventional methods of accessing muscle fatigue such as fatigue questionnaires and watching the workers during work, electromyography (EMG) muscle activity pattern can be a significant technique to explore novel ways to access muscle fatigue without interfering with the ongoing task. Liu et al., [28] performed ergonomic evaluation by recording EMG electrical activity of forearm muscle at different wrist postures for various kinds of wrist rests while using a computer mouse.

After reviewing the literature, it is found that very limited research work has been carried out on ergonomics and fatigue detection monitoring through surface EMG, especially in Pakistan. In contrast to the lab / simulated environment, a real-time in-process muscle fatigue monitoring system development strategy should be worked on for ergonomic evaluation. Researchers have analyzed the EMG signal by extracting features in the time domain and frequency domain but it has been observed that due to the varying nature of the EMG signal results from extracted features in the time domain are more accurate as compared to the frequency domain. Therefore, in this research amplitude analysis in the time domain will be carried out to access muscle fatigue for ergonomics improvement and a novel EMG muscle performance monitoring system is developed to investigate the muscle fatigue levels of employees/workers in different work environments.

III. METHODOLOGY

To develop EMG based performance monitoring system, the proposed methodology is shown in the system schematic figure 1.

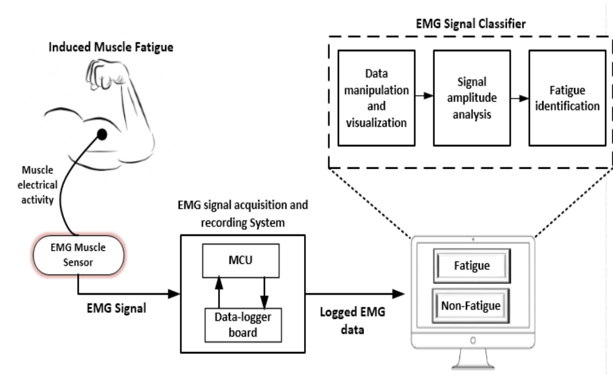

Figure 1: Proposed fatigue monitoring system schematic

Muscle fatigue can be analyzed after performing a task. In this case, fatigue monitoring system is directly interfaced with a computer system, and EMG electrical activity data is recorded and stored in the memory with the help of programming algorithms. However, muscle fatigue can be considered as a real-time dynamic process in which EMG information should be evaluated during a physical exercise/task. EMG muscle activity is recorded using microcontroller unit interfaced with data-logger board and then fatigue is analyzed using a EMG signal classifier.

A. *Data Collection*

A sample of workers/employees will be subjects of the EMG monitoring system. Sticky-type EMG electrodes are attached to the surface of the bicep muscle to acquire the EMG signal. A raw EMG signal has a lot of noise and artifacts associated with it. A high pass filter, Low pass filter, and Bandpass filter are used to acquire the clear signal from the raw EMG signal. The signal is then processed using an analog-to-digital converter (ADC) to convert it into a digital signal. To assess the EMG data, a classifier will be developed to acquire and record the muscle activity of a subject. The program can save the recorded EMG data in memory as a CSV file.

B. *Data Interpretation*

To avoid false interpretation of EMG data it is important to understand this tool. When a motoneuron is activated, electrochemical events generate a muscle-fiber action potential that stimulates the muscle membrane. In response to stimulation, changes in ionic concentration of muscle-membrane tissue produce electrical changes in membrane polarity that are eventually recorded by electrodes. Activation of superficial muscles can be measured with surface electrodes, whereas deeper muscles require more invasive indwelling electrodes. The surface EMG recording represents the algebraic summation of several motor units (a motoneuron and all innervated muscle fibers). To increase muscle-force generation, motor units are activated more frequently and additional motor units are recruited, both of which result in larger EMG amplitudes[29]. In the time domain the fatigue is related to the increment of the EMG amplitude[30] in the frequency domain the shift towards lower frequencies, and in the time-frequency domain when the amplitude increase and spectrum decrease that means fatigue[31].

C. *Data Analysis*

At first, the system is trained by recording electrical activity data from an already fatigued muscle and then compared with the non-fatigue muscle. A threshold value was set by classifying several values above and below the set value as discussed later in the study.

After system training muscle activity data were recorded three times a day on various types of field-work related workers/employees such as Electrician, Fitter, Labor and computer operator, etc. The EMG signal was evaluated through amplitude analysis in the time domain. The increasing trend in EMG signal amplitude shows muscle fatigue and the amplitude decreasing trend show muscle recovery. During real-time in-process monitoring of the EMG signal, the data was continuously stored in the memory. The stored CSV file is fetched from the memory and EMG data is analyzed by the classifier. The EMG signal classifier evaluate the EMG data based on signal amplitude and print output as "Fatigue" or "Healthy" muscle condition. In the end, the developed fatigue monitoring strategy is applied to the case study of gym-goers for the estimation of muscle fatigue.

D. *System Training Methodology*

Adhesive Muscle electrodes of the EMG muscle sensor stick to the muscle and record electrical activity generated by muscle fibers. This electrical activity is recorded in microvolt units of electrical data. But this recorded muscle activity data is also associated with certain losses due to sweat, hairs, skin debris, and sebum on the skin where the muscle electrodes are attached. These factors cause a voltage loss in recorded data although the skin surface of the subjects was cleaned before attaching muscle sensor electrodes. To account for these loss factors, the classifier program needs to be tuned at an optimum value so that the output program can differentiate between fatigue muscle and healthy muscle.

E. *Result Validation Scheme*

Results of EMG muscle monitoring systems are validated through real-time monitoring strategy, in which data was recorded from workers while performing tasks. The EMG electrical activity data can be stored in the memory by integration of Microcontroller unir (MCU) and a Data-logger board. The developed classifier can import CSV files from memory for fatigue analysis and ergonomic evaluation. Afterward, conclusions are made from data using visualization and statistical tools.

IV. SYSTEM DEVELOPMENT AND VALIDATION

To develop our proposed EMG fatigue monitoring system, a classifier for EMG signal data acquisition will be developed. The recorded EMG data is analyzed by the classifier and EMG signal amplitudes of collected data are evaluated in time domain.

A. *EMG Muscle Data Acuisition and Recording*

The Microcontroller unit (MCU) is programmed to read the analog signals and has a built-in analog-to-digital converter (ADC) that reads the varying voltage and converts it to a number between 0 to 1023 which is proportional to the amount of voltage being applied. To scale the analog read number to a voltage between 0 to 5mV, we multiply the sensor value by 5.0/1023.0. The voltage values can be graphically visualize in real-time. The MCU program for reading electrical activity on muscle is shown in figure 2.

```
void setup() {
  // initialize serial communication at 9600 bits per second:
  Serial.begin(9600);
}

// the loop routine runs over and over again forever:
void loop() {
  // read the input on analog pin A0:
  float sensorValue = analogRead(A0);
  // Convert the analog reading (which goes from 0 - 1023) to a voltage (0 - 5V)
  sensorValue = sensorValue * (5.0 / 1023.0);
  String voltageToSend = String(sensorValue);
  // print out the value you read:
  Serial.println(voltageToSend);
}
```

Figure 2: MCU Program for Reading Electrical Activity

To acquire real-time EMG muscle activity of workers during physical activity, MCU and Data-logger board can be interfaced to function as a coherent system. For this purpose, a program is developed for MCU which can record the EMG electrical activity of the fatigue-induced muscle in memory as a CSV file for fatigue analysis by the python classifier.

Microcontroller (MCU) can be controlled with Python IDE. Python is a coding language with the help of which we can analyze and save real-time data. The real-time serial data from MCU can be directly fetched with the help of python and can be stored, analyzed, and plotted by using python programming. The EMG signal plot is shown in figure 3.

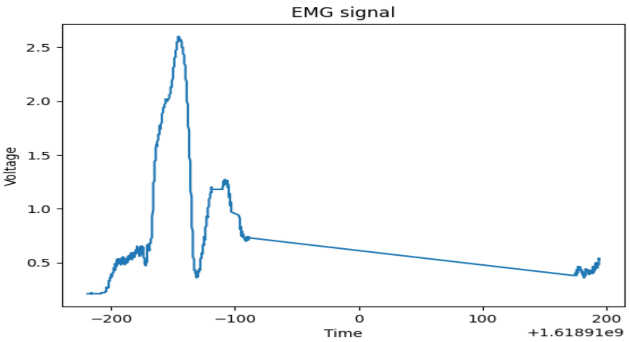

Figure 3: EMG Signal Plot – Voltage(mV) vs Time (sec)

The aim of using python libraries is to save the real-time electrical activity data generated from muscle movement using MCU in the form of a CSV file. Data is stored in the form of comma-separated value file (CSV) files can then be read and analyzed by using a python program.

B. Testing and Evaluation

Classifier programe will be developed for testing and evaluating the previously recorded EMG data. The pandas library is used to read the CSV. files in python. The Concat function is used to combine all the CSV. Files and we can save the resulting CSV. File. Thus, data can easily be analyzed in python as shown in figure 4. The resulting output of combining voltage data of 03 signals and plot of resulted data can be stored in a separate CSV file for further analysis.

```
import pandas as pd
import matplotlib.pyplot as plt


df1= pd.read_csv (r'C:\Users\Clerk\Desktop\csv\test_data1.csv', usecols=['Voltage'])
df2= pd.read_csv (r'C:\Users\Clerk\Desktop\csv\test_data2.csv',usecols=['Voltage2'])
df3= pd.read_csv (r'C:\Users\Clerk\Desktop\csv\test_data3.csv',usecols=['Voltage3'])

data = pd.concat([df1,df2,df3],keys=['Voltage1','Voltage2','Voltage3'],axis=1,ignore_index=True,sort=True, verify_integrity=True)
result= data.head(949)
result.to_csv( "result.csv", encoding='utf-8-sig')
```

Figure 4: Python program for data manipulation

To analyze the EMG signal amplitude, a program is developed in python which can read the CSV file from memory as shown in figure 5. EMG data from CSV files can be analyzed in different data point ranges by the iloc function. Each group of data points can be analyzed by a counter function in python to count the amplitude values above and below the set threshold value. On comparison of amplitude values above and below the threshold value, the program will show the output result as "Fatigue" or "Healthy".

To perform system training, initially, data was gathered from a person with Healthy muscles, and muscle activity data of Fatigue muscle was recorded. The same procedure was repeated 3-5 times and a threshold value was set. The number of values below the threshold and the number of values above the threshold were calculated with the help of the Python fatigue analyzer program. The threshold value needs to be set only once after the assembling of the device for a specific application.

```
df = pd.read_csv('Result_El.csv')
df.rename(columns={'0': 'Morning', 1: 'Afternoon', 2: 'Evening'}, inplace=True)
A=df.iloc[0:3000,1:]
print (A)

for i in A:
    myList = A[i].values.tolist()

    firstCounter = 0.0
    secondCounter = 0.0
    for i in myList:

        if i > 1:
            firstCounter += 1
        if i < 1:
            secondCounter += 1

    if(secondCounter >= firstCounter):
        print("Healthy")
    if (firstCounter >= secondCounter):
        print("Fatigue")
```

Figure 5: Classifier Program to analyze fatigue

Therefore, results were analyzed at different values and the most suitable value will be selected whose output is identical to the physical status of the muscle in actual. For example, if at a set value the output is healthy for a healthy muscle with minimum stress level in actual and program output is fatigue for a high-stress muscle in actual. Then that value will be most suitable as shown in Table I. The threshold value will be calculated by using the statistics library in python program as shown in figure 6.

```
Calculating Threshold.py

from matplotlib import pyplot as plt
from statistics import median

# All suitable Data points of each Trial
suitable_Data_points = [.4,.5,.6,.7,.8,.2,.3,.4,.5,.6,.7,.8,.9,1,1.1,1.2,1.3,.6,.7,.8,.9]
print("Threshold Value of Data is % s" % (median(suitable_Data_points)))

Run: Calculating Threshold
C:\Users\Clerk\miniconda3\python.exe "C:/Users/Clerk/Desktop/Calculating Threshold.py"
Threshold Value of Data is 0.7

Process finished with exit code 0
```

Figure 6: Calculating Threshold value for classifier

TABLE I
SET THRESHOLD VALUE FOR EMG FATIGUE CLASSIFIER PROGRAM

Sr#	Set Value	Known Muscle status	Classifier Output
First Trial			
1	0.3 and below	No physical Stress	Fatigue
		High Physical stress	Fatigue
2	0.4 to 0.8	No physical Stress	Healthy
		High Physical stress	Fatigue
3	0.9 and above	No physical Stress	Healthy
		High Physical stress	Healthy
Second Trail			
1	0.1 and below	No physical Stress	Fatigue
		High Physical stress	Fatigue
2	0.2 to 1.3	No physical Stress	Healthy
		High Physical stress	Fatigue
3	1.4 and above	No physical Stress	Healthy
		High Physical stress	Healthy
Third Trial			
1	0.5 and below	No physical Stress	Fatigue
		High Physical stress	Fatigue
2	0.6 to 0.9	No physical Stress	Healthy
		High Physical stress	Fatigue
3	1 and above	No physical Stress	Healthy
		High Physical stress	Healthy

C. *Result Validation*

Most of the research suggests, measuring the EMG electrical activity of muscles before and after performing a physical task. However, this study's focus is to monitor fatigue in a real-time process that involves continuous measurement of fatigue during a physical task. Pertinent to this, the developed EMG system is tested on a sample of various fields of participants including Electrician, fitter, supervisor, Labor, Officer, and Housewife, and the output results are validated through the python fatigue classifier program as shown in table II. EMG data of all the participants can also be visualized graphically as shown in figure 7.

TABLE II
FATIGUE MONITORING SYSTEMS' RESULT VALIDATION

Field	Time	0-2500	2500-5000	5000-7500	7500-10000	Remarks (L=low, H=high)
Electrician	Day	Healthy	Healthy	Healthy	Fatigue	L-Stress
	Night	Fatigue	Fatigue	Fatigue	Fatigue	H-Stress
Fitter	Day	Fatigue	Healthy	Healthy	Healthy	L-Stress
	Night	Healthy	Fatigue	Fatigue	Fatigue	H-Stress
Labor	Day	Healthy	Fatigue	Fatigue	Fatigue	H-Stress
Bank Teller	Day	Healthy	Healthy	Healthy	Healthy	L-Stress
officer	Day	Healthy	Healthy	Healthy	Healthy	L-Stress

V. IMPLEMENTATION OF DEVELOPED SYSTEM

Figure 12: Python program to analyze fatigue

Gym work-out is a physically demanding task and involves a lot of muscle exertion. Even a small mistake in weight whether it is a wrong posture or angle in lifting weights can result in musculoskeletal disorders (MSD). Gym workout activities are more confounded than they could appear; many elements play a significant part, similar to the technique[32] and its angle of movement. Those variables should be considered to accomplish the objective of working the muscles accurately and ergonomically. One more fundamental element in

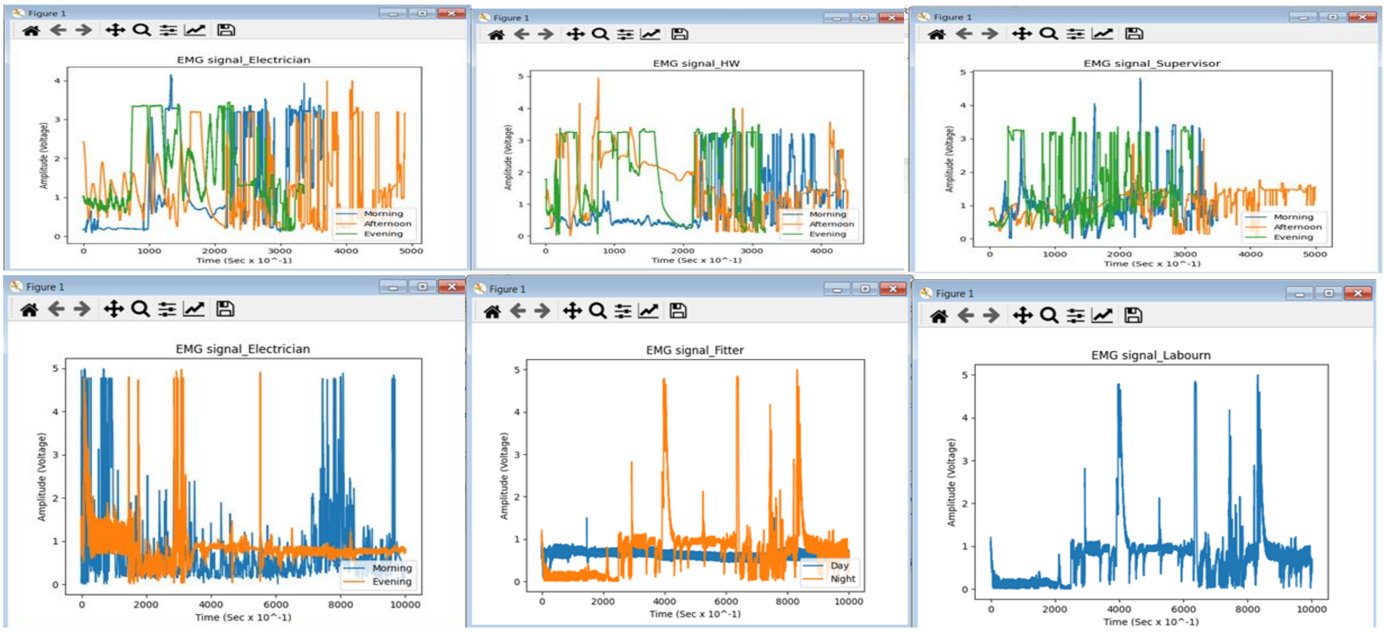

Figure 7: Graphical visualization of acquired EMG data of participants showing increment in amplitude with increase in fatigue

weightlifting practices is to ensure that the weight being lifted is the right one at the particular phase of working out. Weightlifting practices utilizing hand weights or dumbbells should be precisely executed all around, or they will bring about musculoskeletal risks. At times, it tends to be extremely dangerous and may prompt irreversible harm. The majority of the Gym related injuries happen because of free weights improper use, so the exercise strategy should be very accurate. Besides, the answer to this issue is to get an individual weight-lifting trainer to assist with a gym workout and guide you as far as possible, however, this will cost a lot of cash and impossible for every gym-goer out there[33].

EMG signal data of bicep muscle was acquired from Gym-goers for 3-5 minutes while performing gym workouts and their activity performance ergonomics results were concluded. Readings were recorded from random gym-goers while performing gym exercises involving the use of Bicep Muscle. The inclusion criteria of the participants are 20 years or older to minimize injury risks to participants. A total sample size of 11 No. of participants was selected for implementing the developed system. The experiment was conducted in the evening during the summer month of July 2022 at Zoo Culture Gym, Taxila, Pakistan. The demographic characteristics of participants are shown in table III.

TABLE III
PARTICIPANTS' DEMOGRAPHICS

N=11	With Supervision			Without Trainer supervision		
	Age	**Weight (kg)**	**Height (cm)**	**Age**	**Weight (kg)**	**Height (cm)**
Range	24-38	67-94	164-178	20-40	64-83	172-182
Mean	26.6	68.3	146.3	26.4	72.2	175.8
STD	12.7	31.1	63.7	8.2	7.5	4.26

Each induvial was asked whether he perform workout under a supervision or do exercise without supervision before taking reading samples as shown in figure 12. Therefore, Data from three categories were recorded as follows: -

1) 05 participants are gym-goer who exercise without gym trainer supervision.
2) 05 participants are gym-goer who exercise under the supervision of a gym trainer.
3) 01 participant is a gym trainer.

Each EMG voltage signal is analyzed by dividing the signals into 03 groups of Data Points, say the first group (0-1000) and Second group (1000-2000), and the Third group (2000-3000). At the start of muscle movement, the amplitude of the EMG voltage recorded is low which indicates that the muscle is healthy. After a few minutes of exercise with lifting the same load, the Muscles of a few test subjects got fatigued earlier than others, as shown in the results of 2nd group of values. In the 3rd group of data points (2000-3000), the test subjects with bad ergonomics still show a large number of high amplitude values, which depicts their muscle fatigue status while test subjects with good ergonomics are recorded with a high number of low amplitude voltage signals which indicates that their Muscle is Healthy because of implementing good ergonomics in their working environment. Initially, the Muscles readings of almost all test subjects shows a Healthy sign, but after several minutes test subjects involved in poor ergonomics are at risk of musculoskeletal disorder, and the same is analyzed by the classifier. While the program outcome of test subjects with good ergonomics measures have not shown signs of muscle fatigue as shown in table IV.

The monitoring strategy developed to evaluate the performance of workers /employees or an individual from any field of work that can cause muscle stress or fatigue based on ergonomics measures can be used through python code.

The EMG muscle monitoring system can be used to find how much time a break is required in between each set of exercises. The time of each set of an exercise before which muscle can go into fatigue can also be configured to save gym-goers from injuries. Therefore, exercise should be performed under expert supervision.

TABLE IV
EVALUATION OF GYM-GOERS ERGONOMICS BASED ON FATIGUE ASSESSMENT

Description	B/w 0-1000	B/w 1000-2000	B/w 2000-3000	Remarks
Gym-goer without Trainer	Healthy	Fatigue	Fatigue	High- Stress Level
Gym-goer without Trainer	Healthy	Fatigue	Fatigue	High- Stress Level
Gym-goer without Trainer	Healthy	Fatigue	Fatigue	High- Stress Level
Gym-goer without Trainer	Healthy	Fatigue	Healthy	Low- Stress Level
Gym-goer with	Healthy	Healthy	Healthy	Low- Stress Level
Gym-goer with	Healthy	Healthy	Healthy	Low- Stress Level
Gym Trainer	Healthy	Healthy	Healthy	Low- Stress Level
Gym-goer with Trainer	Healthy	Healthy	Healthy	Low- Stress Level
Gym-goer with	Fatigue	Healthy	Healthy	Low- Stress Level
Gym-goer without Trainer	Healthy	Fatigue	Fatigue	High- Stress Level
Gym-goer without Trainer	Healthy	Fatigue	Fatigue	High- Stress Level

CONCLUSION

Muscular fatigue is identified as the most harmful factor that affects workers' ergonomics at the workplace. Real-time fatigue monitoring during a physical task can enhance physical performance and help in preventing accidents. In this study, we investigated a novel approach for developing a fatigue monitoring system based on surface electromyography (EMG). The objective was to enhance ergonomics measures for improving workers' physical performance by analyzing the level of physical fatigue. For this purpose, the experimental setup was developed to acquire EMG signal through muscle sensor and MCU and continuously recorded in memory using a data-logger board. The program is also developed in Python for analyzing the acquired EMG data. In this study, the experimental setup was tested and validated using a real-time monitoring strategy, which is more suitable for monitoring muscle fatigue during physical activity, and EMG data is continuously recorded as a function of time. The research affirms the implementation of the developed EMG system to classify the gym-goers who work out under supervision and without the supervision of a trainer. This study concluded that the surface EMG-based muscle monitoring system is appropriate to detect muscle fatigue or muscle stress levels for enhancing workers' ergonomics measures. The EMG data is recorded using MCU interfaced with a data-logger shield and processed using a classifier. The proposed system is suitable for monitoring, analyzing, and recording data of EMG voltage signals generated by muscle activity.

A. Research Utilization

The proposed EMG system can be utilized in various kinds of jobs to analyze ergonomics measures to minimize work-related musculoskeletal disorders (MSD). With the enhancement of the monitoring system using Python programming language, the developed algorithm is highly efficient in monitoring the stress level of muscles. The approach used in this study can also supplement other muscle fatigue assessment studies. By utilizing the results of this study work-rest schedule can also be designed to minimize work-related stresses on workers, which would result in an increase in employee productivity, better quality work, and reduced absenteeism.

B. Recommendatons for Future Work

Although this study has met its objective of developing an EMG-based fatigue monitoring system. However, there are certain limitations to be considered for future research work. This research work is limited to EMG muscle activity data of the bicep muscle. In the future, neck, back, and leg muscles can also be included in the research scope and work shall be extended to validate this approach with different subject loads and a large group of participants

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interests: None declared
Funding: None
Ethical approval: Not required

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How to cite this article:

Usman Karim Awan and Salman Hussain "Workers Ergonomics Measures Enhancement Through Surface Electromyography (EMG)", International Journal of Engineering Works, Vol. 10, Issue 02, PP. 01-09, February 2023. https://doi.org/10.34259/ijew.23.10020109.