IMPLEMENTATION OF TRIBOELECTRIC NANOGENERATOR (TENG) INTEGRATION FOR MUSCLE ACTIVITY MONITORING

Manat Nursultan, Bachelor in Industrial Automation

Submitted in fulfillment of the requirements for the degree of a Master of Science in Biomedical Engineering

School of Engineering and Digital Sciences
Department of Chemical and Materials Engineering
Nazarbayev University

53 Kabanbay Batyr Avenue,
Nur-Sultan, Kazakhstan, 010000

Supervisors:

Lead Supervisor Name: Associate Professor Cevat Erisken

Co-supervisor Name: Azamat Yeshmukhametov

March 2025

Declaration

I hereby declare that this manuscript, entitled “Implementation of Triboelectric Nanogenerator (TENG) Integration for Muscle Activity Monitoring,” is the result of my independent work, except where due acknowledgment has been made for quotations and citations.

I further declare that, to the best of my knowledge and belief, this work has not been previously or concurrently submitted, either in whole or in part, for any other degree or diploma at Nazarbayev University or any other national or international institution.

I also declare that this research was approved by the Nazarbayev University Institutional Research Ethics Committee (NU-IREC) on 08/04/2025 under submission 1041/18032025. The approval for this protocol is valid until 07/04/2026.

Name: Manat Nursultan

Date: 01.03.2025

Acknowledgements

I would like to express my sincere gratitude to all those who have supported and guided me throughout the course of this research and thesis.

Firstly, I would like to thank my lead-supervisor Professor Cevat Erisken and co-supervisor Azamat Yeshmukhametov, for their invaluable guidance, feedback, and continuous support. Their expertise and insights have been crucial in shaping this work, and I am deeply appreciative of their patience and encouragement.

I am also extremely grateful to the participants who volunteered their time and efforts for the data collection. Their involvement was vital in validating the TENG sensor's performance, and without their cooperation, this research would not have been possible. I appreciate their patience, commitment, and valuable contributions to the study.

I would also like to extend my gratitude to my research colleagues and the entire team at ARMS and Tactile laboratory, whose collaboration and advice were instrumental in conducting the experiments and analysis.

Special thanks to my family for their unwavering support, understanding, and encouragement during the course of my studies. Their belief in me has been a constant source of motivation.

Table of Contents

List of abbreviations

TENG	Triboelectric Nanogenerator
SMA	Simple Moving Average
EMS	Exponential Smoothing
CM	Cumulative Mean
SWF	Sliding Window Filter
MF	Median Filtering
VPP	Voltage Peak-to-Peak
FFT	Fast Fourier Transform
RT	Retention Time
ΔV	Voltage Difference
EMG	Electromyography
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SNR	Signal-to-Noise Ratio
CV	Coefficient of Variation

List of Figures and Tables

Abstract

This work investigates the integration of Triboelectric Nanogenerators (TENGs) for muscle activity monitoring, offering an alternative to traditional methods like EMG and force sensors. The research focuses on the sensor's accuracy, sensitivity, and reliability in detecting muscle contractions across various muscle groups and contraction types. The study incorporates the use of different filters and circuit configurations, including low-pass filters, to improve signal quality and reduce noise. It was experimentally shown that the TENG sensor was able to provide reliable muscle force measurements highly correlated to the force sensor and EMG data. Both extremely slight and extremely large muscle contractions were proven to be sensitive by the sensor, and it exhibited low MAE and RMSE values, doing so accurately. Moreover, the sensor's coefficient of variation (CV) suggested well reproducible values among several trials. Although suffering from some issues, such as signal noise and sensor misalignment, the TENG sensor was successfully used as a wearable muscle activity monitoring solution with the opportunities for applications in healthcare, sports science and rehabilitation. Finally, the study recommends means of future improvements such as sensor optimization, advanced signal processing and integration into smart wearable devices for continuous and real time muscle activity monitoring.

Keywords: Triboelectric Nanogenerator (TENG), muscle activity monitoring, electromyography (EMG), muscle contractions, signal processing, low-pass filters, wearable devices, healthcare, self-powered sensors, signal filtering, circuit design.

CHAPTER 1- (INTRODUCTION)

1.1 Muscle Activity Monitoring

In a variety of applications of biomedical importance, such as rehabilitation, sports science, neurological disorders and prosthetics, it is important to monitor muscle activity [1]. Understanding muscle function, as well as pick up on muscle abnormalities, can give us some valuable information about a patient's health, performance, and their recovery status. The monitoring of accurate muscle activity can help in the diagnosis of neuromuscular disorders, provides optimum training for athletic performance, and assists in the rehabilitation after injuries or surgeries. Over the years, several techniques were developed to measure muscle activity, among which, electromyography (EMG) has been the most widely used [2]. EMG is a measure of muscle electrical activity measured during muscle contraction in real time as a function of muscle function. It is a very useful technique for both in clinical and sports performance monitoring. Nevertheless, there are some drawbacks. However, the attachment of electrodes to the skin or insertion into muscles are invasive and uncomfortable for the patient or subject [3]. It also may suffer from electrode displacement or signal noise created by skin movement which can further corrupt the data. There is also complexity of the equipment, and the interpretation of the data is not for the faint hearted as it requires specialization.

Mechanomyography (MMG) is another way of detecting muscle activity and measures the mechanical vibrations caused by muscle contractions [4]. In spite of the fact that MMG is less invasive than EMG, it is susceptible to external interference and not as accurate in recording slight muscle movement.

Most often, EMG and MMG require external power sources that operate their sensors, restricting system flexibility and comfort [5]. In addition, these methods also need wired connections for data transmission, limiting the movements, and making it difficult to use in real time purposes.

1.2 Problem and research gap

Although biomedical monitoring has been advanced with current muscle activity monitoring technologies such as the electromyography (EMG) and mechanomyography (MMG) and numerous other monitoring technologies, the increase in its analytic complexity necessitates the development of new and improved solutions. Yet, these systems suffer from several challenges that prevent their large scale implementation and operation, most prominently, in noninvasive, continuous and real time detection of muscle activity. Traditional muscle activity monitoring methods, namely EMG, suffer from invasiveness and discomfort of the user, which restricts their long term usability [6]. In addition, skin irritation from these systems or frequent reapplication might inhibit their ability to be used for continuous monitoring. Currently available muscle activity monitoring systems are often too bulky and complex; several sensors have to be worn and need external power supply, thus preventing a widespread everyday use [7]. However, the devices are usually bulky and limit the movement, particularly in physical activity and therefore are not suitable for wearable and real time applications in sports or rehabilitation.

1.3 Overview of modern solutions

Triboelectric Nanogenerators (TENGs) are based on the triboelectric effect, in which electrical energy is produced by contact and separation of two materials with different electron affinities [8]. The end result is charging separation that is used to harvest electrical energy. Firstly, TENGs have several advantages such as being self-powered, they can generate energy coming from mechanical motion without an external power source, which makes TENGs suitable for various wearable and continuous monitoring applications [9]. However, in comparison with conventional instrumentation, their flexibility makes them easy to integrate into various substrates, for example in soft electronics and textiles, and their high sensitivity is necessary for detecting even the smallest mechanical movement important in muscle activity monitoring. Moreover, TENGs are capable of easy and inexpensive mass production utilizing scalable processes like printing or hot molding [10]. Besides muscle activity monitoring, TENGs have been successfully used as motion monitors in smart clothing, sports sensors to track motion and force of physical activity, or environmental sensing that harvests energy from natural movement such as wind or water. TENGs are versatile and are applied in biosensors and self-powered medical devices in healthcare [11].

1.4 Introduction to Triboelectric Nanogenerators (TENGs)

Triboelectric Nanogenerators (TENGs) harvest energy from mechanical energy to electrical energy using a triboelectric effect. If we bring two materials in contact, and they transfer charge as they do so, due to mechanical motion for example contact–separation or sliding, then there will be some type of contact element effect [8]. When the materials are separated, the two material groups can be harvested as useful electrical energy by generating an electric potential between the two groups of materials. Unlike conventional energy harvesting technologies, TENGs do not contain any external power source and uses the energy harvested directly from environmental mechanical motion (vibration, body movement, wind, etc.) to operate [12].

As high voltage and low current generators with the unique property of being self-powered from movement alone, there has been great interest in TENGs for use in such systems. TENGs have the advantages of high simplicity in design, ease in fabrication using common materials and high conversion efficiency of mechanical energy to electrical energy, which makes them ideal for many applications [13]. These devices are especially well suited for wearable technologies or sensor systems where flexibilities grant them ability to be integrated within fabrics or other material that can be conformed to the body to be used towards continuous and real time monitoring of biological signals such as muscle activities. Their self-powered nature and dexterity for integration onto different substrates also improve their suitability in applications such as mobility, low energy consumption and ease of integration.

1.5 Research Objective and Scope

The goal of this system is to enable an easy, noninvasive, continuous real time method to monitor muscle activity that overcomes the problems of the previously proposed EMG and mechanomyography (MMG) methods, which often require an external power source. With their particular properties, including their capacity to create electric signals from mechanical movement, this research pursues the advancement of a TENGs sensor that is sensitive to small muscle movement yet flexible and interferes minimally.

The scope of this study encompasses several key areas:

1. Sensor Design: Optimizing TENG to act as a sensor for muscle activity detection while maintaining high flexibility, durability, and comfort for wearability of long periods time. Sensor placement on the skin or clothing will be taken into account in the design to be able to capture accurate muscle motion data.
2. Data Acquisition: Implementation of a system for Data Acquisition wherein the electrical signals being generated by the TENG sensor is collected during muscle contractions. In this, other circuits also need to be designed to condition the signal, and the TENG sensor needs to be captured in an accurate manner.
3. Signal Processing: Development of algorithms for filtering and processing of the raw data collected from the TENG sensor. It will involve noise reduction methods such as low pass filtering and feature extraction (e.g peak voltage, RMS values) for muscle activity analysis.
4. Validation: The performance of the TENG sensor will be validated against EMG in detecting

muscle contraction and compared to known muscle activity monitoring methods. In order to make sure that the system does in fact work in real world settings, we will be running experimental testing on human subjects.

1.6 Scientific novelty and significance

This research contributes to the scientific aspect by promoting the integration of Triboelectric Nanogenerator (TENG) in such a muscle activity monitoring system, whose execution is not present in existing literature. However, for such a system to be truly mobile, or even in the others sense, solutions are needed for self-powered, non-invasive, and flexible sensors to continuously monitor muscle activity without external power sources or complex setup. This solution mitigates critical drawbacks of EMG and MMG techniques which largely operate in a power dependent, uncomfortable, and complex regime. This research is of particular importance in the fields of healthcare, sports science, and rehabilitation. Continuous monitoring of muscle activity in healthcare can be useful in early diagnosis and treatment of neuromuscular diseases, as these can deliver real time muscle function and recovery information. Such a system could be used to monitor the progress of rehabilitation in patients, evaluation of therapy, or personalization of treatment plans. In sports science, monitoring muscle activity in real time while the athlete is training leads to performance optimization and injury prevention through, for example, identifying muscle imbalance or early detection of fatigue to prevent injuries [14].

This research also advances the application of TENGs beyond energy harvesting as a practical health monitoring wearable device and contributes to the broader field of wearable health devices and self-powered systems [15]. The improvement of TENG-based muscle activity sensor design in wearable sensor technology also contributes to the integration of energy efficient solutions in daily use healthcare. Compared with existing wearable health devices, which suffer from the drawback of requiring frequent charging or replacement of the batteries, TENGs are potentially ideal for long term, continuous monitoring due to their nature of self-powered devices [16]. Additionally, TENG sensors are flexible as well as comfortable that can be easily integrated into daily wearables like clothing or accessories for long term monitoring.

CHAPTER 2 - (MATERIALS AND METHODS)

2.1 Sensor Design and Development

2.1.1 Material Selection

The selection of materials while designing the triboelectric nanogenerator (TENG) sensor for monitoring muscle activity was also done with enough care to enable the generation of an electrical signal when it is mechanically stimulated [17]. Eco-flex, carbon cloth and electrode wire are the primary materials which are incorporated into this sensor system and are selected based upon their distinctive properties and defining features to optimize sensor system performance [18].

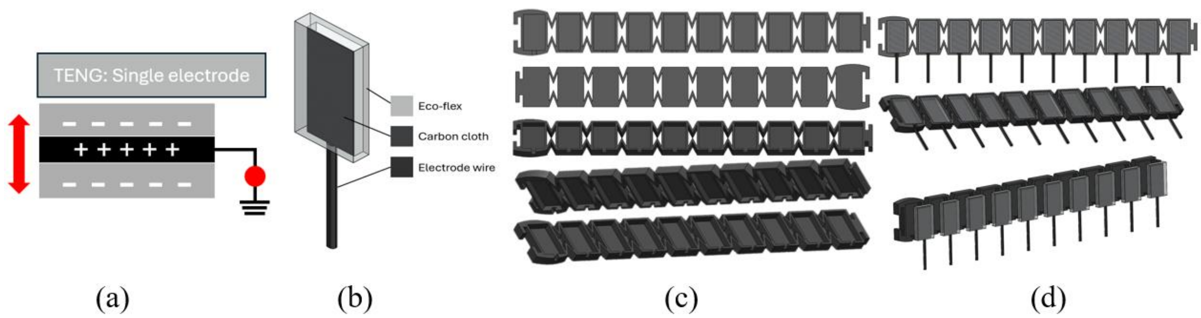


Figure 1. Visual of the Sensor with Expandable and Contractible Housing Bracelet: (a) TENG sensor scheme; (b) TENG sensor; (c) Various angles of the sensor housing; (d) Visualization with sensors placed inside the cells.

Figure-1 depicts a single-electrode configuration of a triboelectric nanogenerator (TENG), a device that harnesses mechanical energy through the triboelectric effect. In this setup, the TENG consists of a central electrode that interacts with two different materials, represented by the alternating "+" and "-" symbols [18]. These materials, upon mechanical motion (indicated by the vertical red arrows), experience a charge separation due to contact and separation, leading to the generation of a voltage. The motion, typically involving pressing or stretching, causes the materials to exchange charges, creating a potential difference between the electrode and the surrounding environment. The single electrode configuration means that only one electrode is used to collect the electrical signal generated by this process, as opposed to a dual-electrode system. The red circle and line denote the ground connection, which completes the circuit for signal measurement or energy harvesting. This is a configuration that is used widely in self-power systems in which energy is produced directly from the mechanical stimulus. The image shows the model of triboelectric nanogenerator sensor (TENG) for muscle activity monitoring, as well as a 3D model of a sensor bracelet for sensors to be mounted into. Three components of the sensor are composed of Eco-flex, Carbon cloth, electrode wire. The eco-flex acts as a flexible encapsulating material that safeguards the sensor against destruction and use in various shapes and surfaces. The new sensor consists of a core made from carbon cloth that acts as the core where the electrical signals are generated when the material is subject to any mechanical stimulus, which might be muscle contractions for instance, that also employs the triboelectric effect. The electrode wire is critical in the conduction of the generated electrical signals for the electrical signal to be easily collectable and transmitted.

The bracelet consists of 10 expandable and contractible cells, each designed to securely house a sensor. In (b) of the model reveals the bracelet housing from a few perspectives, and in the second part of the figure (c) the visualization further includes the location of the sensors within the cells. The flexibility and adaptability to various usage conditions, for instance, muscle activity or other mechanical forces, come from bracelet's stretching and compressing along its length. The structure is robust to remain held in the desired position, yet the transition of the shape to the needed dimensions for effective operation is allowed.

Finally, the sensor bracelet is designed and can be 3D printed using TPU (Thermoplastic

Polyurethane) which is a flexible material that can provide both durability and comfort at the same time [19]. The bracelet is made of a series of expandable and contractible cells that securely contain a sensor that can be easily dismounted or replaced when necessary. The stretchable design of the bracelet works well and comfortably fits on the wrist, whose contour it interlocked. The model can be adjustable for various wrist sizes and can be made smaller or larger in the model before printing. While flexible, the design keeps the sensors aligned properly during use so data can be collected reliably, yet comfortably and with a good range of motion. The dynamic and user–friendly wearable design is suitable for continuous monitoring to be worn by the user.

2.1.2 Sensor Geometry and Configuration

In order to create an accurate model for TENG behavior and to optimize their performance, an understanding of their operation is necessary. A widely used method for this purpose is use of the Norton equivalent circuit model, where TENG is represented as a current source in parallel with capacitive reactance [20]. This model permits a simple analysis of the TENG output, especially in regard to how the output depends on load resistance and open circuit voltage generated by the device. The circuit model of the output current I_{out} is then as below:

$$I_{out} = \frac{V_{oC}}{R_{\mathrm{load}}} \tag{2.1}$$

where:

- V_{OC} is the open-circuit voltage.
- R_{load} is the load resistance.

Finally, the presented model depicts how an external load is supplied with current by the TENG depending on its open circuit voltage and external load resistance. By analyzing this relationship, the efficiency and behavior of the TENGs in practical application connected to a load becomes known.

In the equation (2.1), the output current I_{out} is related to the open-circuit voltage V_{OC} and load resistance R_{load} by the formula:

This model relates the voltage V, charge Q, and displacement x of the TENG:

$$V = \frac{Q}{C(x)} \tag{2.2}$$

where C(x) is the capacitance as a function of displacement x.

The displacement current I_D is a key driving force for TENGs:

$$I_D = \frac{dQ}{dt} = \frac{d}{dt}(C(x)V) \tag{2.3}$$

In this case, Q is the charge and C(x) is the capacitance as a function of displacement x. Since ID depends on the time derivative of the product of C(x) and V, which are related to the motion of the TENG and its electrical response, it can be optimized by using an appropriate time change function V(t) [21].

From this, we can see that the output current I_{out} as a result of the output voltage and load resistance, is governed by the displacement current ID that is driven by changes in the capacitance and displacement. The effect of generated TENG voltage on the output current and displacement current due to mechanical motion determines the efficiency and performance of energy harvesting process. Therefore, the displacement current is shown to be the enabler of the output current in TENG and the analysis of it is important to optimize it as the output source for TENG based systems.

2.1.3 Fabrication Process

Triboelectric nanogenerator (TENG) sensor fabrication consists of a well-controlled sequence of steps for controlling the quality of materials used for performance and durability [22]. The Eco-flex material used in this sensor design is one of the key components to it, being flexible and durable materials. The fabrication process firstly involves the preparation of Eco-flex mixture, which would be prepared in order to achieve the right Eco-flex mixture for optimal sensor functionality. Correct measurement, mixing and degassing procedures are included in order to guarantee the properties of the material are accurate and suitable for muscle activity monitoring.

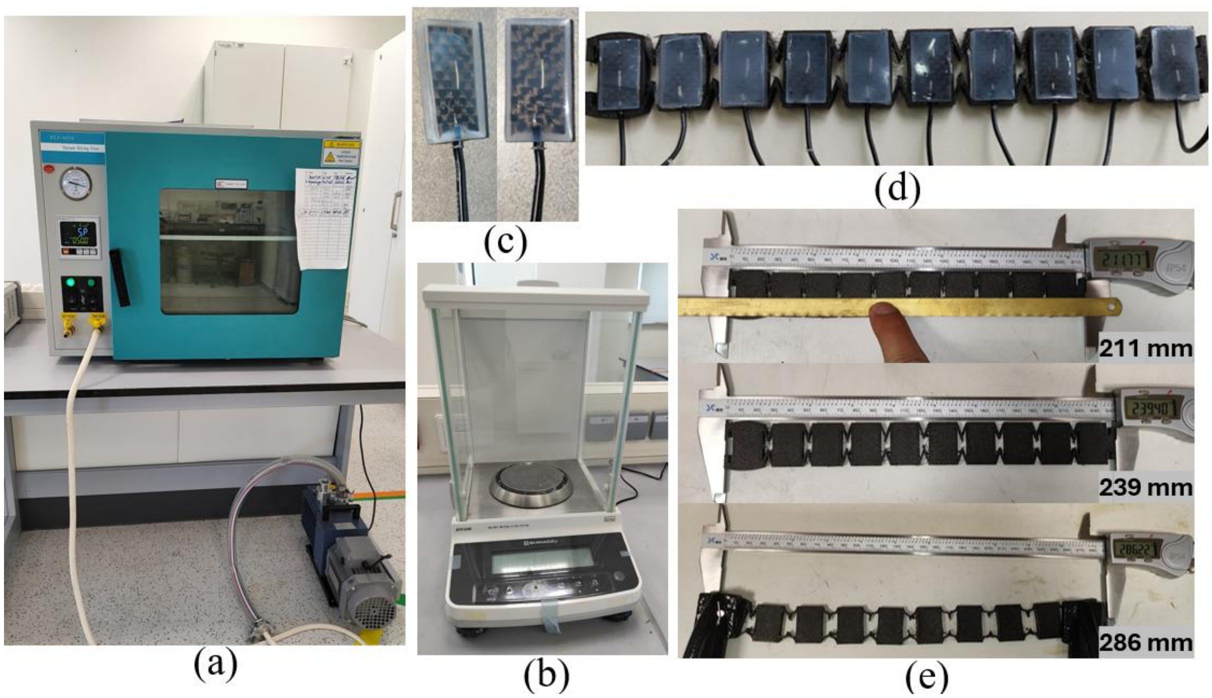


Figure 2. Fabrication of the Sensor Bracelet with Expandable and Contractible Housing: (a) Vacuum oven with pump; (b) Digital scales; (c) Individual TENG sensor module; (d) The full sensor bracelet assembly; (e) Size measurements of the bracelet at different stretch points.

First, components of eco-flex parts A and B are mixed. After this, the mixture goes through a mixing process wherein thorough stirring is performed to equip it with uniform consistency and also to get rid of air bubbles. Two Eco-flex components are weighed in 1:1 ratio on a digital laboratory scale before mixing them. A precise measurement of this prevents the components being mixed in the wrong proportion, which is essential for the desired material properties and consistency. After mixing, the material is placed in a vacuum oven at 25°C for 5 to 10 minutes under a vacuum to remove any remaining air bubbles and to ensure the Eco-flex mixture is fully degassed.

The real version of the sensor bracelet designed for monitoring showed in figure-2. Panel figure-2(c) shows the individual sensor module, which fits into each expandable cell of the bracelet. Figure-2(d) illustrates the full sensor bracelet with multiple sensor modules arranged in a sequence, demonstrating the flexibility and design of the wearable. Panel (e) depicts the bracelet mounted on a circular form, showing its adaptability to different shapes while still maintaining sensor placement and connectivity. Panel figure-2(d) demonstrates the size measurements at various stages of the bracelet's expansion and contraction, with sizes of 211 mm, 239 mm, and 286 mm recorded under different stretch conditions. The TPU material used for this design enables the bracelet to tailor to varying wrist sizes and to be worn for long periods of time for reliable data collection in dynamic environments.

Having looked at the design, it has been ensured that the sensors remained constant in its performance regardless of the bracelets expansion or contraction without effecting to the signal accuracy or stability. The bracelet is designed to also be comfortable to wear for long periods of time, with adjustable stiffness and angles able to be customized by the user which results in a more comfortable and providing better performance.

The TENG sensor has no power supply except from itself, while the control arm needs an external power source (a battery), which will be included in the bracelet in the future versions, reducing the size and increasing usability [23]. It can transmit data from the sensor via Bluetooth with the ability to allow wireless capability and connect to other external devices. The bracelet combination of features enables it to be an efficient and adaptable wearable for continuous monitoring.

2.2 Experimental Setup

2.2.1 Test Environment

Several RC circuit configurations were used for test environment established to evaluate the performance of TENG sensors and to analyze how different filtering techniques affect the output signal of the sensor [24]. Designed configurations were aimed at assessing the signal quality of this sensor and for optimization towards the applications of muscle activity monitoring.

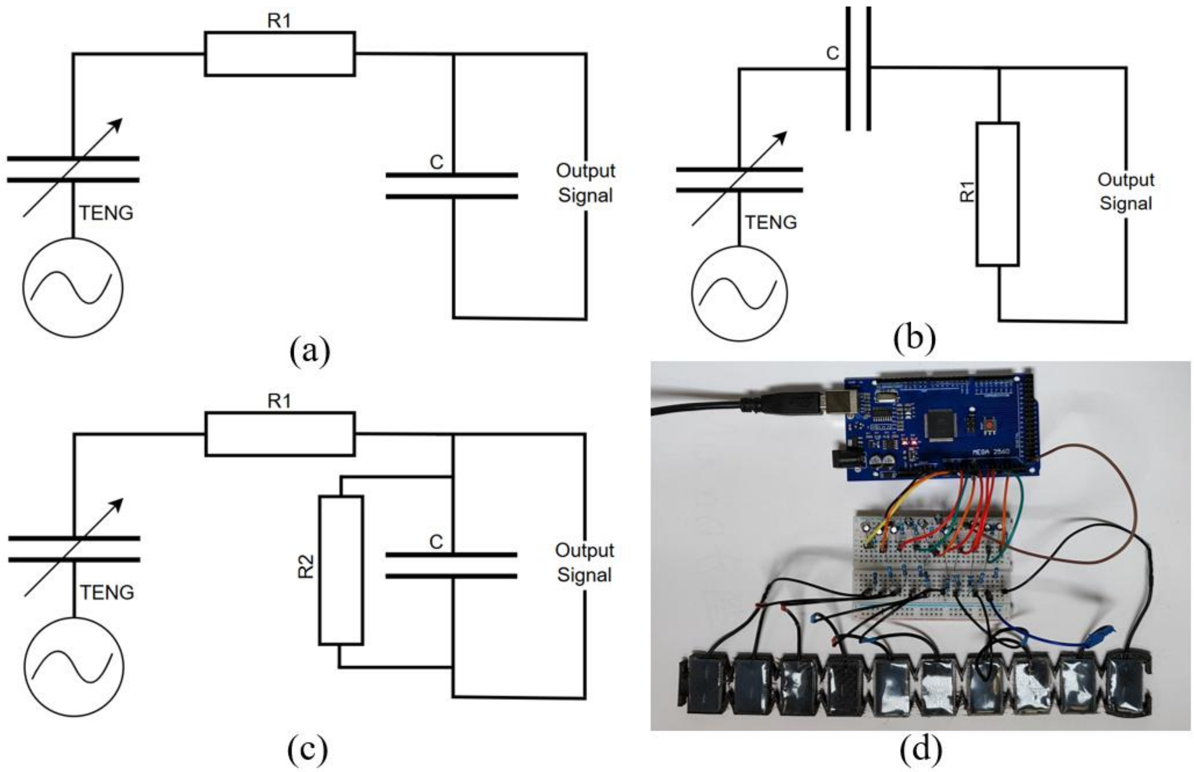


Figure 3. Circuit Configurations and Hardware Setup for TENG Sensor Testing: (a) Low-pass filter; (b) High-pass filter; (c) Low-pass filter configuration with an additional parallel resistor; (d) Hardware setup.

Different configurations of RC circuits for testing the output signal of the TENG sensor and analyzing the effects of filtering are first presented in Figure-3. In part (a), the TENG sensor is applied in a low-pass filter configuration with the resistor (R1) and capacitor (C) [25]. With this setup, low frequency signal can pass, but would filter out higher frequency components, thus smoothing the signal. The second part (b) shows a high pass filter configuration, this means that higher frequency signals are allowed to pass though while rejecting lower frequencies. In part (c), the circuit is a low pass filter with the comparisons in parallel as a resistor. The parallel resistor modifies the filter's shape by varying the rate at which the capacitor charges and discharges and therefore influences the filter's signal processing characteristics [26]. To argue the validity of the experiments, part (d) depicts the hardware setup utilized for the experiments, with the Arduino microcontroller connected to different TENG sensors—a breadboard is used for doing the same. With these TENG sensors, the real time processing and analysis of the signals that they generate are achieved via filtering of the circuit configurations. In order to test the effectiveness of each filtering method, a series of configurations are tested to optimize the signal output from the muscle activity monitoring applications.

2.2.2 Mechanical Stimulation

In this work, we used servo motors to simulate muscle contractions to offer a controlled and repeatable mechanical stimulus that can be utilized to test the TENG sensor. The servo motors were chosen for their ability to accurately control the speed and force of movement and reproduce the type of pressure and motion exerted from human contraction muscle [27]. To ensure each data collection session was standardized with consistent time intervals, and mechanical forces it was decided that we would alter the speed at which the servo motor would move its contact into the TENG sensor and change the degree of force with which the contact made contact with it.

Programmed the servo motor to perform several muscle activities, namely, rapid muscle contractions (fast short presses) and sustained muscle contractions (slow long presses). To simulate, various levels of muscle exertion, the contact force that was applied to the TENG sensor was varied so that the sensor response could be tested over an entire range of reasonable conditions. This setup provided the data collection in a reproducing manner, reducing the impact of external parameter (e.g.

muscle fatigue, irregular movement). The servo motor's speed, displacement and the contact pressure were carefully controlled and, to ensure the consistency of the test scenarios, also mechanically parameterized to guarantee the precision and reliability of results. For instance, the motors actuation capabilities would be able to simulate human muscle characteristics within a torque range from 0.1 Nm for smaller muscle groups to more than 20 Nm for larger ones. The motors could sustain the required load for the experiments. Because of this, the speed of the servo motors was calibrated to ride at 60 to 300 degrees per second to approximate human muscle fiber contraction rates (fast or slow twitch muscle fibers). A resolution of 12 bits (4096 discrete positions) ensured precise control, allowing fine adjustments in muscle contraction mimicry. Digital servo motors with position feedback (such as encoders) provided accurate control and replication of proprioceptive feedback, essential for realistic movement simulation. The servo motors were tested across various contraction types, including both rapid bursts and sustained contractions, to ensure comprehensive muscle activity simulation, which allowed for consistent, reproducible data collection, thereby enabling a thorough evaluation of the TENG sensor's performance.

2.3 Data Acquisition System

Figure-4(a) shows the successive phases of interaction with the TENG sensor corresponding to the experiment. In the first section (0-15 seconds), a series of rapid touches is observed, expressed in the form of frequent signal peaks, which indicate high-frequency exposure. The second section (20-35 seconds) demonstrates a similar nature of the signals, but for a longer time, confirming the stable response of the sensor to prolonged touches. In the third section (40-60 seconds), the tempo of touches is reduced, which is reflected in less frequent and smoother peaks, indicating slow interactions. The fourth section (65-90 seconds) is characterized by hold touches, where the signal reaches and maintains a stable high voltage, creating long plateaus on the graph. The intervals between sections

(15-20, 35-40, 60-65 seconds) show pauses without activity, marked by a signal close to zero. The graph clearly shows the differences in the types of interactions, reflecting the changes in frequency, amplitude and duration of the signals in each section.

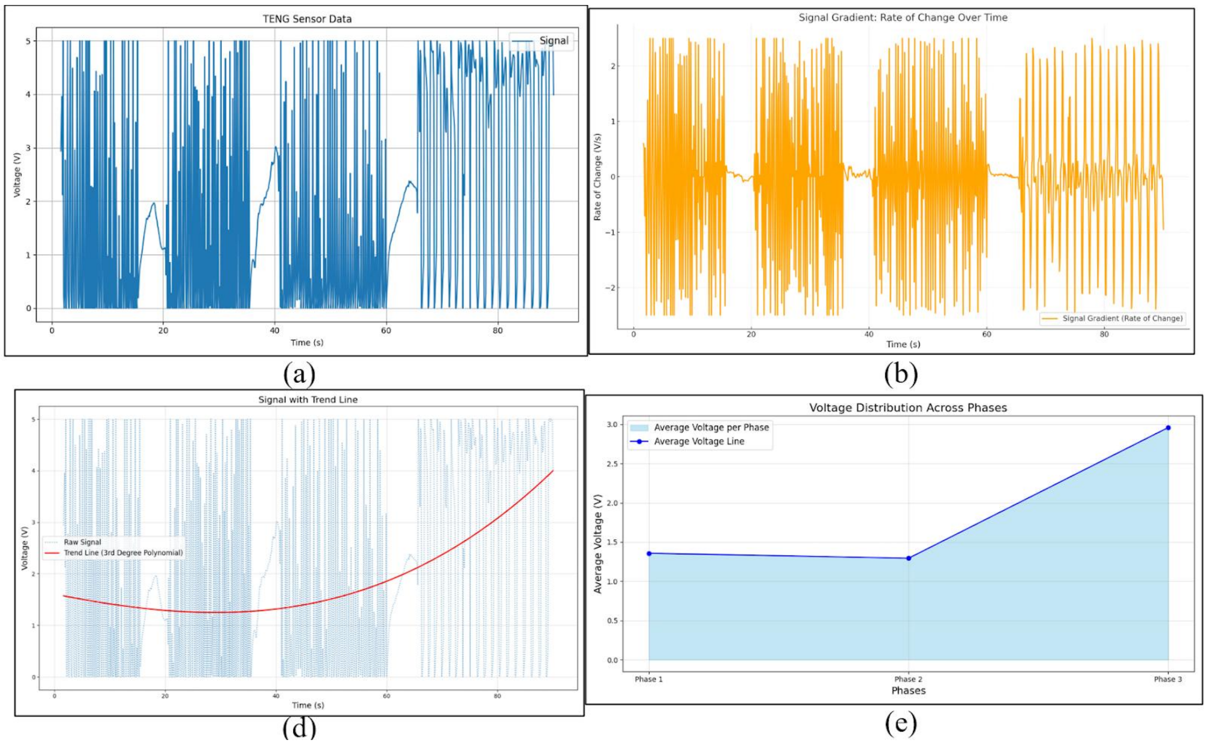


Figure 4. TENG sensor's data plot: (a) Voltage Value over 90 sec time; (b) Gradient Over Time Signal Dynamics; (c) Polynomial Trend Line; (d) Average Signal Voltage Across Interaction Phases.

The reason for this is because the voltage derivative, or gradient, indicates the rate of voltage change per time and is thus an important tool to use when analyzing TENG sensor data [4]. It enables signals to point out the portions of abrupt changes distinctive of touches or quick motions as well as isolate the periods of action and retention. Dynamic changes such as increase or decrease in voltage are associated with high values whereas the values are low for stable phases such as voltage retained. The dynamic signal dynamics, instabilities, periods of activity and passivity, and noise and artifacts are all assessed with this. However, it may help to analyze the strength, speed and stability of muscle contractions, and to identify characteristic changes during different phases of a task of monitoring muscle activity.

Many areas in the figure-4 (b) can be seen with sharp peaks or both positive and negative directions, therefore indicating rapid voltage changes. It can be associated with active phases of interaction of these sites. Stable phases of the signal are related to areas with an almost horizontal line or low gradient fluctuations. It is clearly visible that these are distinctions between periods of high activity (sharp gradient fluctuations) and periods of low activity (small gradient amplitude). Positive gradient values are indicative of rapid increase in voltage, whereas, negative values refer to rapid decrease of voltage. This can be attributed to the change in the force of impact on the sensor or to the change of interaction conditions.

To establish a trend line when TENG sensor signals are analyzed, it is to identify the global change and the general signal trend [5]. This is a way to smooth out data by omitting small variations and noise to pay attention to long term variations. Polynomial approximation is used to do the trend line, minimizing the deviation between real data and approximating function. One of the main reasons for using a trend line is to first get the overall pattern of a signal to grow (or decline), or that it tends to remain stable, which is useful for long—term patterns on sensor activity. Abstraction from local fluctuations makes possible focusing on key properties of signal, whereas particularly important while evaluating the sensor operation or investigating the interaction dynamics with it. In Figure 4-c the dotted line shows voltage changes, including all small fluctuations, noises and emissions that occur when interacting with the TENG sensor. The red line smooths the data, highlighting the overall trend of the signal. The graph shows that at the beginning the overall trend decreases, then stabilizes, and increases again towards the end, which may indicate an increase in activity or a change in the conditions of interaction.

The graph in Figure-4(d) shows an area diagram showing the distribution of the average voltage across three phases of the signal: Phase 1, Phase 2 and Phase 3. The first two phases demonstrate a stable average voltage of about 1.5 V, which may indicate uniform activity or retention of the signal. In the third phase, there is a significant increase in the average voltage to 3 V, which indicates a change in the type of interaction, for example, increased activity or increased force on the sensor. The blue area visualizes the contribution of each phase, and the blue line highlights the changes between phases, reflecting the overall dynamics of the signal.

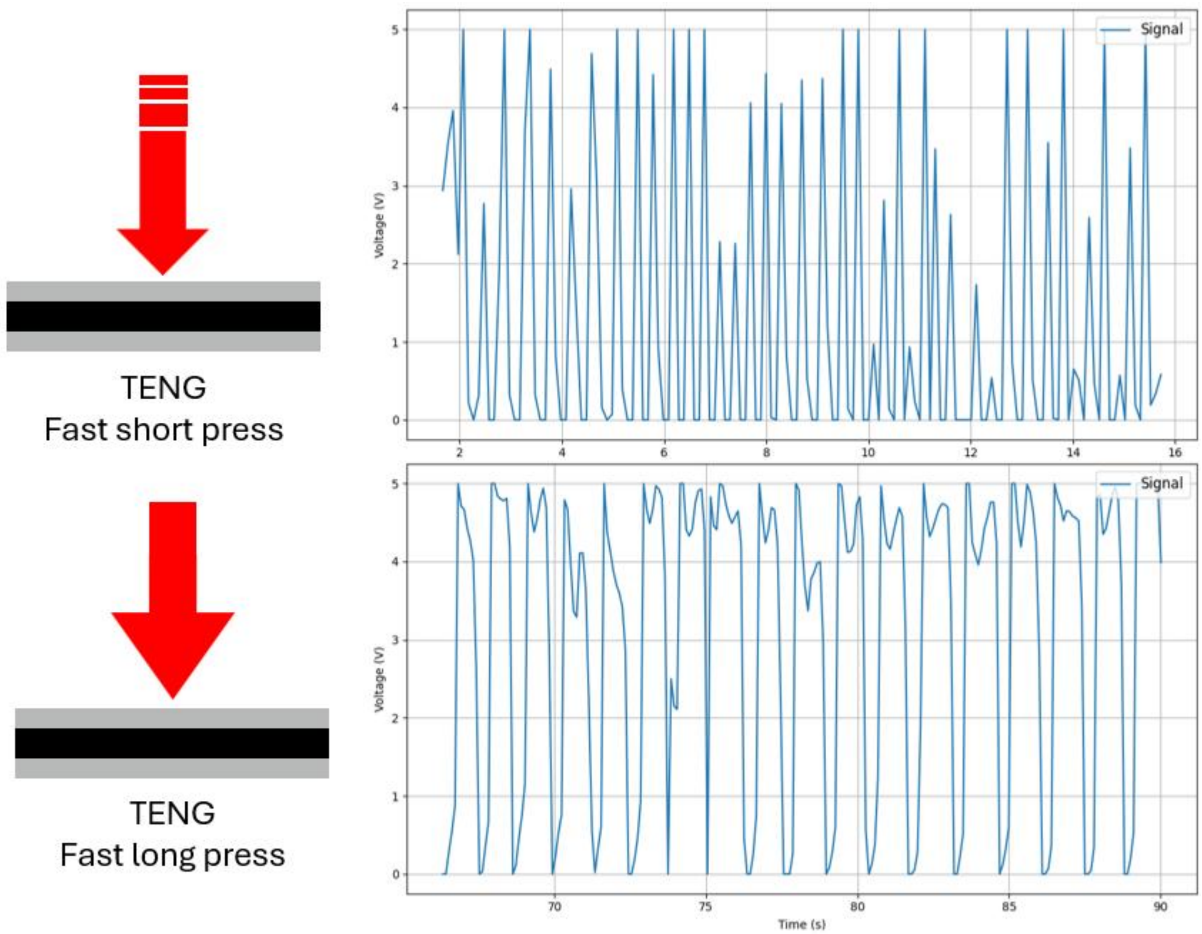


Figure 5. TENG Sensor Response to Fast Short and Long Presses.

In Figure-5, the response of a TENG sensor to two different type of mechanical pressing stimuli is shown: fast short press and fast long press. The physical actions displayed on the left are images with the upper image depicting a fast short press and the lower image a fast long press applied to the TENG sensor. The corresponding time signals are shown on the right side. The signal of the fast short press is fast voltage further fluctuated and has very high frequency peaks, which implies that a fast short successive mechanical presses. However, the lower signal in the bottom graph has less frequent, but more sustained fluctuations to represent a fast long press, which has a longer duration and continued application of pressure on the sensor. Observations are made to show that these pressure variations can be detected by the sensor, and the signal provides insight on the triboelectric response of the TENG sensor.

The working of a triboelectric nanogenerator (TENG) in a circuit is based on Kirchhoff's law [28]. Depending on the way the circuit is configured with load resistor, capacitors, and other circuit elements, whether they are active or passive, TENG generates a current. Kirchhoff's current law and voltage law are applied to the system to derive the equations of this behavior.

$$\mathrm{I_L} + \mathrm{R_L}\frac{\mathrm{dI_{LC}}}{\mathrm{dt}} = \mathrm{I_N}$$
$$I_{D,C} = R_L\frac{dI_{IC}}{dt} \tag{2.4}$$

Where:

- I_L is the current through the load.
- I_{LC} is the current through the internal capacitor.
- I_N is the current source representing TENG.

These equations result from applying Kirchhoff's voltage law to the load and capacitor components in the circuit. The presented models are utilized in understanding and simulating the behavior of TENGs for various operational conditions and explaining how a TENG performs in energy harvesting and sensor applications.

When mechanically stimulated, TENGs create electrical signals that relate to the displacement current which is the amount of the accumulated charge per unit time. The displacement current is intimately related to the variation in the capacitance and the voltage of the system, which is then a means of quantifying the sensor response to mechanical motion. This section explains how analyzing the displacement current, through its mathematical formulation explaining how the time derivative of the capacitance and voltage product governs the electrical output of the TENG. The displacement current $I_D(t)$ is given by:

$$I_D(t) = \frac{dQ(t)}{dt} = \frac{d}{dt}\big(C(x)V(t)\big) \tag{2.5}$$

This equation shows that the displacement current is related to the rate of change of the charge Q(t) over time, which in turn depends on the time derivative of the product of the capacitance C(x) (a function of displacement x) and the voltage V(t).

The next step is to integrate the displacement current to find the charge:

$$Q(t) = \int I_D(t)d\,t \tag{2.6}$$

By integrating the displacement current over time, we obtain the total charge Q(t), which is accumulated due to the displacement current.

The charge is then substituted into the voltage formula:

$$V(t) = \frac{(\int I_D(t)d\,t) \cdot d(x)}{\epsilon A} \tag{2.7}$$

Thus, by d(x) is meant the displacement with respect to position, e is the elementary charge, A is the cross-sectional area. As shown, the voltage V(t) is expressed as a function of integrated charges and the displacement as well as other system parameters.

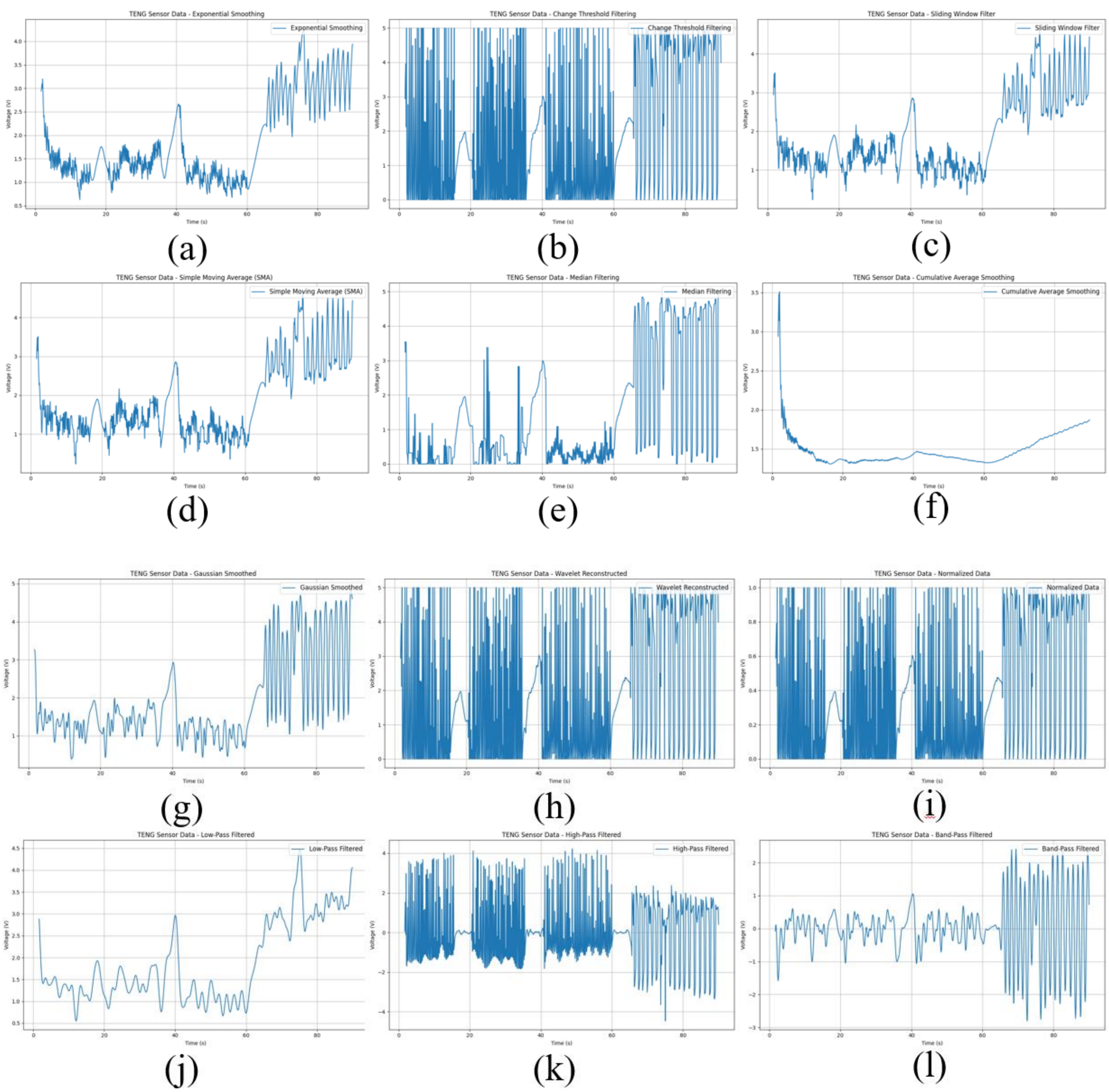
Essentially, the equations describe the mechanical displacement in the TENG carried with the generation displacement current, the charge accumulation and induced voltage. Since the displacement current can be integrated to find the charge as a function of time, we will find a means of computing the voltage generated by the TENG.

2.4 Signal Processing Techniques

2.4.1 Noise Filtering

Appropriate noise filtering was conducted to the raw data of TENG sensor to reduce noise and improve the signal quality for better analysis. Due to contamination with high frequency noise, the raw signals captured by the TENG sensor are frequently correlated with other residual signals such as the true muscle signal or the sensor response. Some of the methods to overcome this problem include filtering the data with several filtering methods to smooth out the data and remove unwanted noise although, they all are suitable for different types of data with particular application requirements.

Several data smoothing and filtering techniques are applied to the raw TENG sensor data and shown in Figure-6. Panel (a) is Exponential Smoothing, which helps smoothing the data by assigning more weight to recent observation. Change Threshold Filtering, shown in panel (b), uses some threshold above which abrupt changes are filtered out. The results are presented in Panel (c), which shows the application of a Sliding Window Filter where one passes a window of fixed size over the signal over time to smooth. Simple Moving Average (SMA) on panel (d) provides a starting method of taking an average of data points on a sliding window. Fig. Panel (e) shows the application of Median Filtering, where each data point is replaced by the median value in a sliding window in order to trim the outliers. The last one is Cumulative Average Smoothing, which computes the average of all preceding values up to the current point to gradually smooth the data. Gaussian Smoothing (panel (g)) proceeds to remove more high frequency noise but preserve the overall trend of the signal. In (h), Wavelet Reconstruction expresses the signal as a sum of wavelet coefficients and simply reconstructs the signal, getting high and low frequency components. Normalized Data are shown in Panel (i) in which the signal values have been scaled to a certain range to facilitate comparison of different datasets or conditions. The data shown in panel (j) is the Low-Pass Filtered Data, where high frequency noise is filtered out without loss of the low frequency components. In Panel (k), the first thing that is filtered away is low-frequency drift from the data, and only rapid changes in the signal is plotted (which is the High Pass Filtered Data). Finally, panel (l) shows Band-Pass Filtering, which consists on maintaining frequencies within a given range and discarding the low and high frequency noise, ensuring isolation of pertinent signal components.



(a) (b) (c)
(d) (e) (f)
(g) (h) (i)
(j) (k) (l)

Figure 6. Comparison of Data Smoothing and Filtering Techniques Applied to TENG Sensor Data: (a) Exponential Smooth; (b) Change Threshold; (c) Sliding Window; (d) Simple Moving Average; (e) Median; (f) Cumulative Average; g) Gaussian Smooth; (h) Wavelet Reconstruction; (i) Normalized Data; (j) Low-Pass Filter; (k) High-Pass Filter; (l) Band-Pass Filter.

They demonstrate the effectiveness of various methods in getting rid of noise and enhancing signal clarity for proper analysis of the TENG sensor data. More general noise reduction was provided by Change Threshold Filtering and SMA, but the most effective in preserving important signal features was Exponential Smoothing and Median Filtering. Due to application specific requirements, the choice of filtering method depends on the noisy signal of interest, thus more aggressive smoothing methods are better suitable to remove general noise, and E.S. is the ultimate option for certain real time applications, where recent signal trends seem to be more important.

2.4.2 Feature Extraction

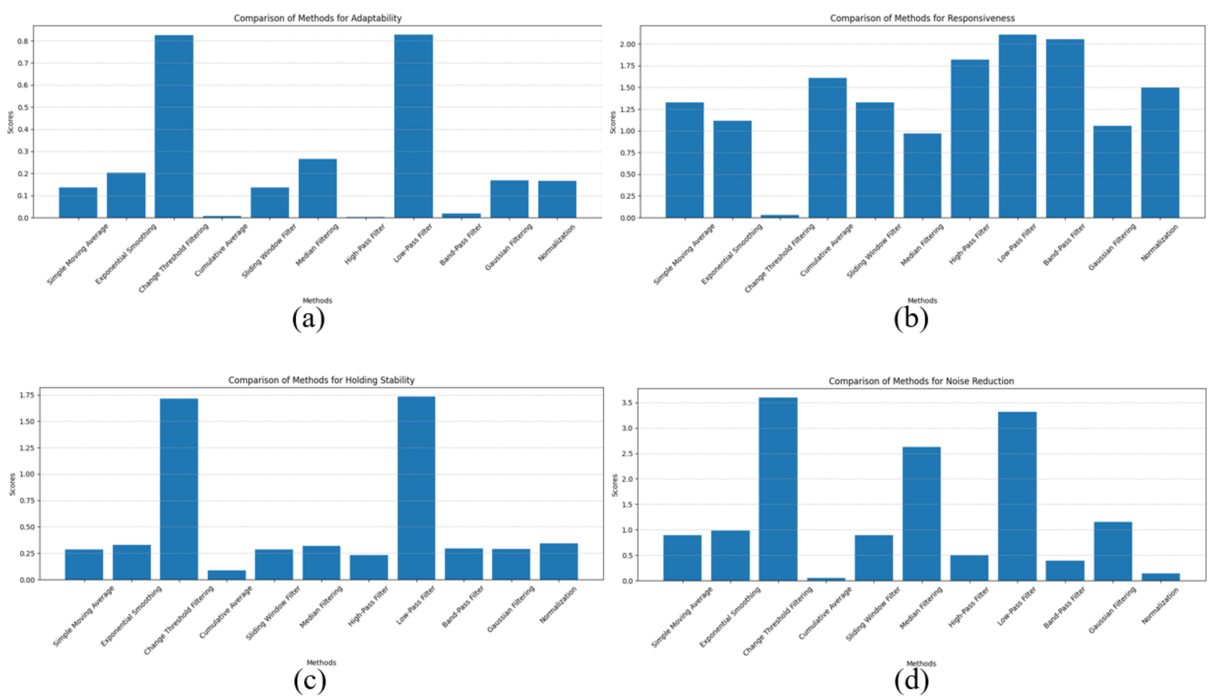
To interpret the TENG sensor signals, it is necessary to filter the data and extract the features that are relevant. The process of finding the key characteristics of the signal that allow distinguishing between levels of muscle contraction as well as muscle force quantification. The purpose of feature extraction is to extract significant patterns inside the raw data correlated to different muscle activities like muscle contraction and relaxation. For feature extraction, this study uses Peak Voltage, Root Mean Square (RMS) Voltage and Frequency Analysis as the techniques [29][30].

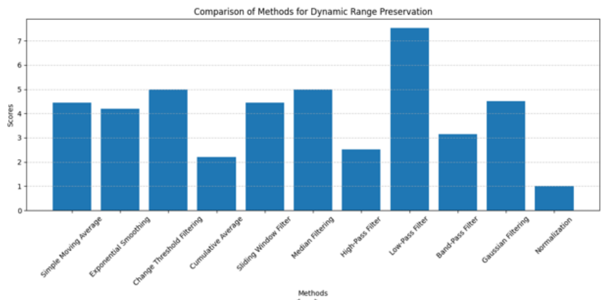
Then the filtered signal is utilized to extract the peak voltage that signifies the maximum voltage generated by a muscle contraction. For example, this feature can be very handy for detecting the strength of muscle activity, since generally the voltage amplitude is related to the force produced by the muscle. Peak voltage is usually defined as the maximum value of the signal in some time window during a muscle contraction. The peak was either the absolute maximum value of the signal (giving the highest point during a contraction), or the maximum value excluding any baseline fluctuations (enough criterion to separate contractions from baseline noise). As such, the intensity of muscle contraction is evaluated based on absolute peak in many cases. If consistency is required, peak voltage can be taken over the muscle contraction phase. It therefore means it pulls out this peak on an active contraction phase and not based on the muscle relaxation phase.

The Root Mean Square voltage is obtained for a measure of signal's total energy or power. This is an important feature to determine muscle activity intensity and it may be used to monitor variations in muscle contraction pressure. Calculating RMS using a sliding window can be useful if muscle activity is changing or changing over time. RMS can be used to capture changes in contraction intensity by applying it over small, overlapping windows. However, it is particularly important for the case when the muscle is active nonstationary. For non-stationary signals like rapid changes in muscle contraction strength, baseline shifts or high-pass filtering prior to calculating RMS are sometimes necessary to remove low frequency noise from the signal so that the signal represents muscle activity and not noise. To determine the frequency components of the filtered signal, Frequency Analysis, Fast Fourier Transform (FFT) is used [31]. By knowing this, we are able to identify patterns correlated to frequency of muscle contractions (fast twitch or slow twitch fibers, etc.) The periodicity of muscle activity can further be observed in the frequency spectrum, that may provide a means for differentiating between different muscle movements. The sampling rate could affect its frequency resolution. However, according to the Nyquist Theorem, we need a sampling rate of at least twice of highest frequency of interest to have an accurate frequency analysis [32]. When it comes to muscle activity, frequencies are often in the range of few Hertz to hundreds Hertz, therefore it is important to ensure that the sampling rate is high enough that can record these frequencies. Different types of muscle fibers can be associated with certain specific frequency ranges. For example, fast-twitch fibers generate frequency components of higher frequencies because of fast contractions, and slow-twitch fibers have lower frequency components. For this purpose, it is typical to band pass filter the signal such that it concentrates on the frequencies of the relevant muscle activity.

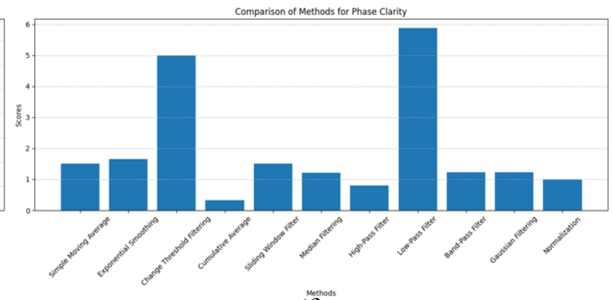
2.4.3 Data Analysis Algorithms

In this section, several important aspects for evaluating performance of sensors used to monitor muscle activity, including six major aspects, are compared thoroughly for different data smoothing methods applied for TENG sensor data.





(e)



(f)

Figure 7. Comparative Analysis of Smoothing Methods Across Key Aspects: (a) Adaptability; (b) Responsiveness; (c) Holding Stability; (d) Noise Reduction; (e) Dynamic Range Preservation; (f) Phase Clarity.

A Comparative Analysis of Smoothing methods on TENG sensor data (Figure-7) has been performed for six important parameters, namely, Adaptability, Responsiveness, Holding Stability, Noise Reduction, Dynamic Range Preservation, and Phase Clarity. Adaptability is highest for the Low-Pass Filtering and Change Threshold Filtering, as these are the two filters that are most able to adapt to changes in signal condition. Both of these methods perform well because Low-pass Filtering mainly preserves low frequency components and Change Threshold Filtering effectively picks up on significant changes in the signal. Whereas, Simple Moving Average (SMA) and Exponential smoothing is less adaptable as it has a more rigid behavior to dynamic change. The most responsive types are Low-Pass Filtering, Band-Pass Filtering and High-Pass Filtering since they truly capture rapid signal changes and preserve key features over different frequency ranges. However, these methods are more sensitive to fast transitions of the signal and therefore are applicable also in some dynamic problems. Conversely, both Cumulative Average and Simple Moving Average have a bad responsiveness since they smooth out or select up on cut quick progressions in the signal. Low-Pass Filtering and High-Pass Filtering are again the best for Holding Stability by reducing both high frequency noise and low frequency noise to ensure the same signal over time. Thus it assures a sufficiently stable and dependable signal to be ensured for prolonged use. Gaussian Filtering and

Simple Moving Average make the data smoother which means they will smooth out the important fluctuations making the data less consistent. In the field of Noise Reduction, Change Threshold Filtering does a great job of eliminating high frequency noise from the signal without harming the signal itself. On the other hand, this technique works excellently in separating noise and signal fluctuations. However, less effectiveness is achieved in noise reduction since normalization and Gaussian Filtering do not target towards the noise frequency resulting in poor filtering. Low-pass Filtering tops the list in terms of Dynamic Range Preservation, it preserves the complete amplitude of the signal and attenuates any unnecessary high–frequency noise. It is ensured this way that the variability and important features of the signal are preserved. Conversely, Normalization and Cumulative Average methods do not preserve dynamic range well, as they squash or scale down the signal and loss amplitude variations. In Phase Clarity, as in previous filters, Low-Pass Filtering and High-Pass Filtering preserve most communication of timing and structure in the phases of the signal. These filters are essential for applications that make use of phase transitions, for example, muscle activity monitoring or mechanical sensing. Because they tend to smooth sharp changes in the signal, Exponential Smoothing and SMA scores are lower in terms of phase clarity. In general, Low-Pass Filtering stands apart as the most flexible technique, excelling both in individual terms and across the board in adaptation, responsiveness, holding stability, dynamic range preservation and phase clarity. In Noise reduction Change Threshold Filtering is stood out because it is suitable for those cases that require noise to be eliminated. However, these methods like Simple Moving Average and Gaussian Filtering perform low across these criteria and thus, may not be the best technique for TENG sensor data analysis, thus the need to select suitable filtering technique depending on the application requirements.

Since the sensor consists of monitoring muscle activity, the selection of the filtering techniques has to be made so that slow muscle contractions (low frequency change) as well as fast muscle movement (high frequency change) are captured. Filtered out noise and simultaneously preserved low frequency components related to muscle holding or sustained contractions is of special interest if one is interested in Low-Pass Filtering. Noise from sporadic spikes, which are common in muscle-related signals that are subject to movement or external interference, will be removed by Median Filtering.

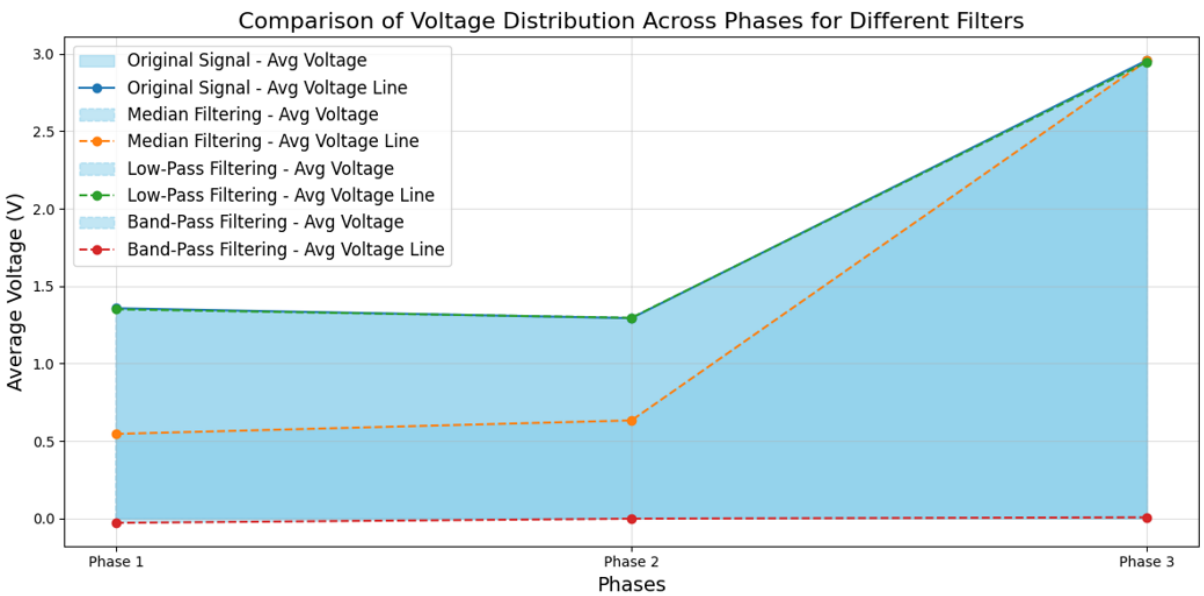


Figure 8. Comparison of Voltage Distribution Across Phases for Different Filters.

This figure-8 demonstrates the distribution of the average voltage across three phases of TENG sensor signal: Phase 1, Phase 2, and Phase 3. A comparison of the original signal and filtered ones with filtering methods such as median filtering, low pass filtering and band pass filtering is done with the help of area diagram. Each phase is a different phase of the cycle of the given signal. From this graph, it is clearly seen how average voltage values in these phases are affected using each of the filtering techniques. In the blue area, we show the raw signal, which contains arbitrary voltage fluctuations over time (hi frequency noise, as well as random spikes). In this report, this signal is regarded as the real-time sensor performance without any smoothing or noise reduction. The orange dots represent the median filter, which is a noise remove method which replaces each given data point with the median of assigned neighboring values the within a given window. It thus produces a smoother signal that has removed the outliers and noise but retains meaningful voltage changes. For instance, low-pass filtering as shown by the green dots is interested in removing high frequency components and retaining low frequency trends. The smoothness of the voltage distribution resulting is smooth with gradual transitions between the phases. For applications where long-based trends or slow signals variations are of interest, such as in the monitoring of muscle activity over extended time, this filter is useful. The red dots indicate band-pass filtering, which passes only a range of the frequencies of the middle-frequencies of the signal. The focus is on the specific features of the signal that can be beneficial for identification of specific events or oscillations when the frequency noise is inside the filtered frequency band. This allows us to compare the impact across these filtering techniques as applied to the signal. The Median Filtering eliminates the noise in the signal by smoothening, the Low Pass Filtering captures such long term trends and the Band Pass Filtering isolates certain frequency ranges for further analysis.

2.5 Calibration and Validation

2.5.1 Calibration of the TENG Sensor

Calibration of the TENG sensor is necessary so as to ensure the sensor's capability to yield accurate muscle force measurements. Its purpose is to relate the TENG sensor's electrical output to the muscle force occurring during the muscle activity. Apply a low pass filter to remove high frequency noise. An example of transfer function for a Butterworth filter is:

$$H(s) = \frac{1}{1 + \frac{s}{\omega_c} + \left(\frac{s}{\omega_c}\right)^2 + \cdots + \left(\frac{s}{\omega_c}\right)^n} \tag{2.8}$$

Where:

- s: Complex frequency variable.

- ω_c: Cutoff frequency.
- n: Filter order.

The Butterworth filter is designed to have flat frequency response in the passband, and the signal will not be distorted in the range below the cutoff band but effective to high frequency component above. After the unwanted high frequency noise is filtered out of the signal, meaningful features are extracted from the filtered signal. One of the features in one can extract is the peak voltage which is the highest value of filtered signal:

$$V_{\text{peak}} = \max\left(V_{\text{filtered}}(t)\right) \tag{2.9}$$

This calculation helps identify the highest point in the signal, which may correspond to significant events or activity in the system being monitored, such as muscle contractions in the case of a TENG sensor system.

Relate the extracted features to physical parameters. For instance, for modeling muscle activity, a simple linear relationship might ne used:

$$F_m = k \cdot V_{peak} \tag{2.10}$$

This model allows the conversion of the voltage signal generated by the TENG sensor into a meaningful physical quantity—muscle force—by establishing a direct proportionality between the two.

Where:

- F_m: Estimated muscle force.
- k: Calibration constant.

The model's predictions must be validated against experimental data to ensure its accuracy. The error between the estimated muscle force $F_{m,\ estimated}$ and the experimentally measured muscle force $F_{m,\ experimental}$ is calculated as:

$$Error = |F_{m,\ estimated} - F_{m,\ experimental}| \tag{2.11}$$

This validation step quantifies the discrepancy between the model's predictions and real-world data, providing a measure of the model's performance. A smaller error indicates that the model accurately represents the relationship between the voltage signal and muscle force, while a larger error suggests the need for further refinement or recalibration

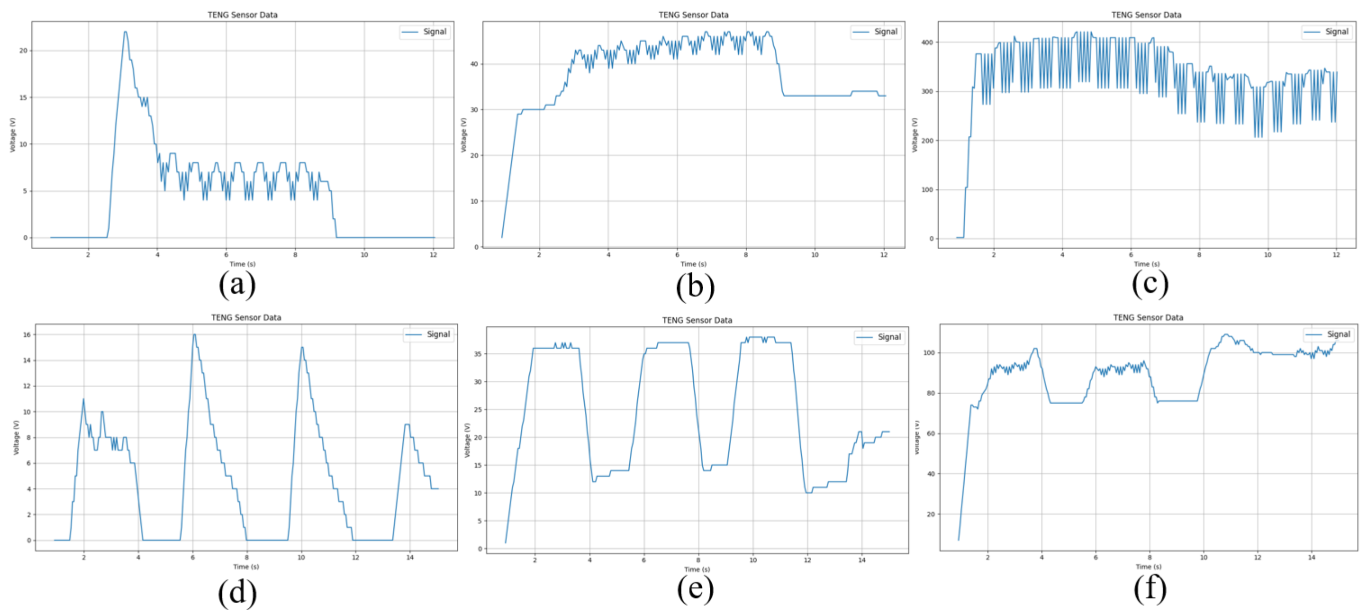


Figure 9. TENG sensor data with Butterworth Low Pass Filter: (a) Low-Pass Filter with Parallel Resistor (Single Contraction); (b) Low-Pass Filter without Parallel Resistor (Single Contraction); (c) No Filter (Single Contraction); (d) Low-Pass Filter with Parallel Resistor (Multiple Contractions); (e) Low-Pass Filter without Parallel Resistor (Multiple Contractions); (f) No Filter (Multiple Contractions).

Figure-9 presents the TENG sensor data collected during hardware testing under different circuit configurations. Figures (a), (b), and (c) show the sensor's response to a prolonged muscle contraction, lasting from 2 to 8 seconds, followed by muscle relaxation. In panel (a), the sensor is connected through a Butterworth Low Pass Filter with a parallel resistor to the final capacitor, while panel (b) shows the sensor connected to the same low-pass filter, but without the parallel resistor configuration. Panel (c) depicts the sensor's response without the use of the Butterworth Low Pass Filter. Figures (d), (e), and (f) display the data for multiple muscle contractions occurring in time intervals 1-3s, 5-7s, 9-11s, and 13-15s. The sensor which is connected to the Butterworth Low Pass Filter with a parallel resistor is represented on panel (d), panel (e) uses the same filter without the parallel resistor and panel (f) is the data without the filter. In these cases, the performance of the sensor and the effect of the filter and resistor configurations on the signal can be evaluated as it relates to noise reduction and signal smoothing in the example of monitoring muscle activity.

Table 1. Response and Holding Time Comparison for Different Circuit Configurations

Circuit Configuration	Resistor (Ω)	Capacitor (μF)	Response Time (ms)	Holding Time (s)
Low-Pass filter	4.8kΩ	0.1μF	0.3	1.95
Low-Pass filter	4.8kΩ	0.22μF	0.4	2.3
Low-Pass filter	4.8kΩ	0.47μF	0.5	2.48
Low-Pass filter	1kΩ	0.1μF	0.2	2.6
Low-Pass filter	1kΩ	0.22μF	0.3	2.9
Low-Pass filter	1kΩ	0.47μF	0.4	3.22

Table-1 presents the comparison of different low-pass filter configurations based on resistor and capacitor values, along with their respective response time and holding time. The type of filter used is indicated in the circuit configuration column and it is always a low pass filter in this case. The table shows the variation in the resistor and the capacitor values: the resistor varies from 4.8kΩ to 1kΩ; the capacitor takes value from 0.1μF to 0.47μF. Response time specifies measure how quickly the circuit active on change of the input signal. Interestingly, a higher capacitance does lead to a slight increase in time as seen by 0.47μF having a higher response time than 0.1μF. The holding time is the time during which the sensor's output is stable after the muscle contraction. Regardless, configurations with 0.47µF capacitors (which provide higher capacitance and lower resistance) thus have longer holding times (3.22 seconds with 1kΩ resistor). When the capacitance grows bigger, the response time is also magnified. As an example, when the capacitance is equal to 0.1µF, the response time is 0.3ms but rises to 0.5ms when capacitance is changed to 0.47µF. The effect of resistor value, relative to each other, has a relatively small impact on response time, but 4.8kΩ had slightly greater response times than the 1kΩ. Large capacitors will in turn, give longer holding times, so that the sensor will maintain a constant output for as long as possible after the muscle contraction. Since the longest holding times (2.48s with 4.8kΩ resistor, and 3.22s with 1kΩ resistor) result from the 0.47µF capacitor, it is interesting to see the capacitor holding times. With 0.1µF capacitors, holding times are shorter (1.95s with 4.8kΩ resistor).

2.5.2 Validation Methodology

To determine if TENG based sensor can give accurate, reproducible and significant information about muscle activity monitoring, its performance must be validated. The results of sensor's output are compared with electromyography (EMG), traditional methods, for assessing its accuracy, sensitivity and reliability in different experimental conditions in order to achieve this. Therefore, the process of validating the TENG sensor involves calibrating the TENG sensor to correlate its output to muscle force or muscle activity. To achieve this, a reference force sensor or EMG system is used as a baseline for the muscle activity. There are muscle contractions performed during the calibration (e.g., isometric contractions) and the corresponding voltage of the TENG sensor is recorded. The EMG or force sensor readings are then compared to the collected data to generate calibration curve, which maps the raw output (e.g., voltage) of the TENG sensor to force or activity levels. For practical applications in healthcare and rehabilitation, it is crucial that TENG sensor can detect the muscle force and activity accurately, which requires this calibration.

After the calibration step, the performance of the TENG sensor is validated by analyzing the output of the TENG sensor against the EMG signals during isometric contractions, dynamic movements and muscle relaxation. In comparing the amplitudes, signal shapes and time response of raw signals from both TENG and EMG systems, the ability of the TENG sensor to track muscle activity is characterized. Both the TENG and EMG signals are analyzed and the key features, namely peak voltage and root mean square (RMS) voltage, are extracted. The ability of the sensor to detect muscle contractions and quantify the intensity of the activity is then evaluated by comparison of these features. Furthermore, application of the Fast Fourier Transform (FFT) is performed on both of the signals to see the frequency components of them in order to determine how optimal the TENG sensor is in tracking the frequency of muscle contraction and discriminating between fast and slow twitch muscle fiber activity.

The TENG sensor is evaluated for its sensitivity by measuring what is the smallest reliably detectable muscle contraction it can sense. The response of TENG sensor is first tested by gradually changing the applied force or displacement to it. It also compares how fast the TENG sensor can response to the muscle contractions, especially the rapid muscle movements. Signal-to-noise ratio is measured to quantify sensitivity to measure that the TENG sensor is capable of sensing low intensity muscle contractions, as well as reduce noise.

In the accuracy testing, the sensor TENG output is compared with the reference systems and the mean absolute error (MAE), the root mean square error (RMSE) between TENG and EMG signals are obtained. The correlation coefficient (R) is also computed to assess the correlation between the two systems (i.e. the TENG data and the EMG data) and quantifies strength of that relationship. With this, a precise evaluation can be made about how close the TENG sensor is to tracking under the measurements of conventional methods.

2.6 Experimental Protocols

Finally, we ensure that the test subjects themselves are properly prepared—we are required that the TENG sensor system is correctly adhered to the subjects' body and also that the experimental conditions for every subject are consistent. The next stages show how participants are prepared and how muscle activity is recorded in the experiment:

1. Finally, we ensure that the test subjects themselves are properly prepared—we are required that the TENG sensor system is correctly adhered to the subjects' body and also that the experimental conditions for every subject are consistent. The next stages show how participants are prepared and how muscle activity is recorded in the experiment.
2. Loose clothing should be worn by participants so that the muscle groups to be tested (such as the forearm, bicep or quadricep) can easily be accessed. Before placement of the sensor on the target muscle groups, the skin is cleaned to maximize good skin sensor contact so as to minimize oils or sweat that may reduce signal quality.
3. The TENG sensor system may take the form of a bracelet made of elastic rubber material which fits around the wrist or forearm. The muscle activity is directly monitored by built in sensors into this bracelet. Furthermore, other muscle groups or body parts are covered with additional removable sensors according to the experimental needs. The individual sensors are secure to the body using rubber Velcro and so will not move or cause discomfort during movement.
4. Muscle activity tasks are performed using muscle movement instructions to participants.

Chapter 3 – (RESULTS)

3.1 Experimental Setup

3.1.1 Test Subjects

Test subjects used in this study were chosen to have a representative sample for the evaluation of the performance of the TENG based sensor for muscle activity monitoring. The following describes the participants' demographic information, inclusion criteria, and ethical considerations:

- Age: The sample was healthy adults of 18 to 40 years, typical of age group in which the muscle strength and endurance were normal. To focus on individuals who do not yet have age related muscle degeneration, but naturally may have variable muscle activity at this age, this age range was chosen.
- Gender: The participants of the study were both male and female, in order for the results to apply to both genders. To minimize the presence of gender related bias in muscle activity monitoring, an effort was taken to care for the counterbalance between males and females.
- Physical Condition: The participants were all healthy individuals, none were suffering from any kind of musculoskeletal disorders. Since it was crucial to avoid the complications or confounding factors of an actual muscle condition, and determine typical muscle activity, this was important.

The research was conducted in adherence to principals of ethical practice as set by the Institutional Research Ethics Committee (IREC). Prior to the start of the study, ethical approval had been received. Comprehensive information throughout study objectives, procedures and any potential risks were given to all participants. The risk was small, some minor discomfort from sensor placement or muscle activity task.

3.1.2 Sensor Placement

To detect accurate muscle activity, TENG sensor was placed on biceps, forearms and triceps because these muscle group are prime for both dynamic and static muscle activity and can be the best option of monitoring. Due to their frequent use in tasks where muscle activity must be performed with a force and fine control motor pattern, these muscle groups are suitable for testing muscle activity with varying contraction patterns. The TENG sensor was then fixed to the muscles with a rubber bracelet design. For individual sensors, Velcro straps were used in some cases for easy attachment and removal.

To alleviate such restriction, the TENG sensor was placed over the belly of the muscle, biceps or triceps, or forearms, where muscle contraction is most visible. As such, this placement guaranteed that the sensor will be sensitive to both dynamic and static muscle activity. The sensors was also aligned to the direction of fibers within the muscle, so they could sense mechanical deformations given during muscle contractions.

Figure-10 shows how the TENG sensor is attached on the participant arm with the sensor array wrapped around the arm and connected to the microcontroller. On the right the corresponding signal sees a flat line, since there is no mechanical stimulation or muscle contraction at that moment, so there is very little voltage generated from the TENG sensor. In the bottom image, we see that the participant contracts a muscle or makes some movement advised by the position of the sensor. In the right exhibit, the signal goes up and down, peaks and valleys that the TENG sensor detects shows mechanical energy generated from muscle contractions. The sensor responds to these voltage variations as the result of muscle activity and extracts the associated mechanical energy of the muscle movement and converts it into electrical signal for further analysis. The performance on real time, noninvasive muscle activity monitoring among such TENG–based sensors is shown in this setup.

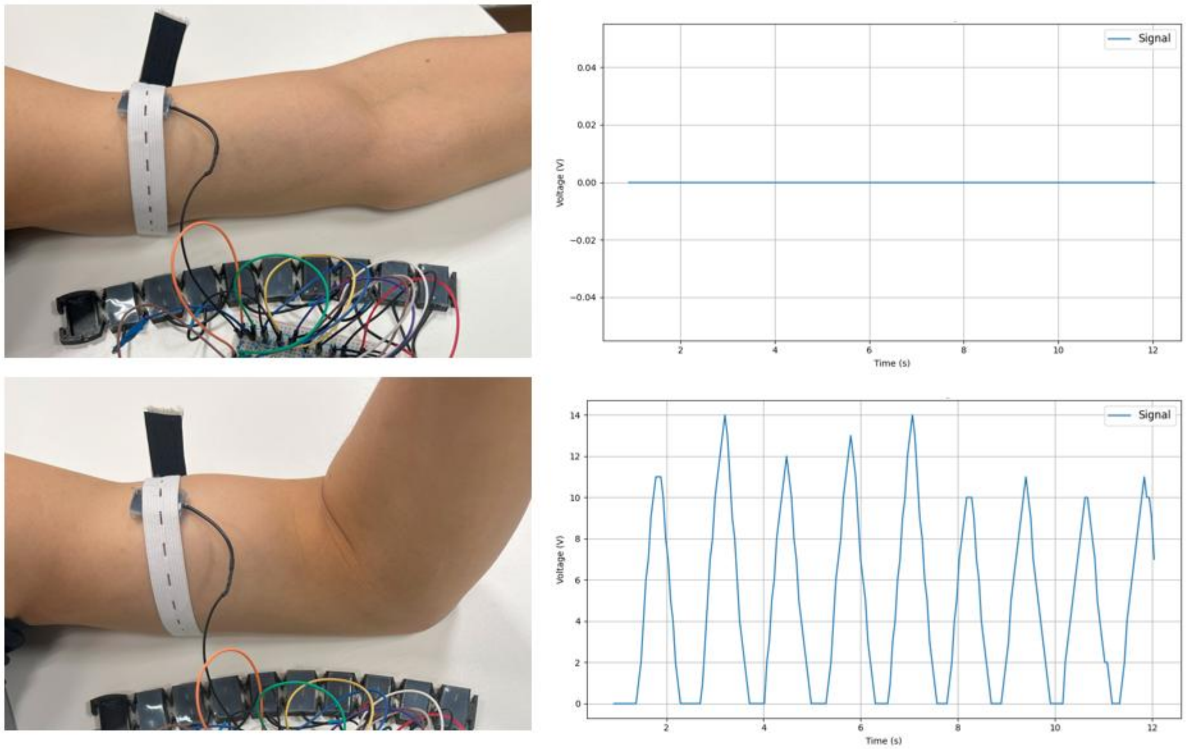


Figure 10. Experimental setup for monitoring muscle activity using a TENG sensor.

3.1.3 Mechanical Stimulus

To ensure that the sensor's ability to detect and measure muscle activity was assessed across different types of muscle contractions, the mechanical stimuli included various types of contractions, i.e., isometric, isotonic, and dynamic contractions. The participants performed isometric contractions, holding a certain muscle position, but with no change in length of the muscle. Participants had to maintain a static muscle contraction while the arm was held at a fixed angle. Force levels were varied from low exertion, eg., holding a light weight, to maximal, such as holding the arm still under significant load. The contractions were held for a period of time standardized between 5 and 10 seconds (to simulate sustained muscle activity).

Participants exercised, performing contractions with both muscle shortening and lengthening, for isotonic contractions. The exercises included, for example, lifting and lowering a weight, both concentric and eccentric phases of muscle activity. These movements were controlled by the force (although the force applied was provided by the weight involved and the intensity was determined by the resistance). To approximate physiological muscle activity during resistance training, each contraction duration was standardized.

Participants performed muscle contractions in the dynamic movement phase that are similar to arm flexion and extension or quick muscle exertions. Therefore these movements were meant to support fast twitch muscle fiber activity, which means fast contractions. These movements were at a moderate to high force level and ranged from 1 to 3 seconds per cycle.

3.2 Signal Comparison with EMG

3.2.1 Raw Signal Comparison

A comparison of the amplitude of the signals from the TENG sensor and from the EMG system was made to measure the intensity of muscle contractions. The higher voltage EMG signals are of relatively smaller magnitude compared to TENG sensor signals and are prone to variations with changes in placement of electrodes and a patient’s skin impedance.

Since both systems provide quantified data, the difference in shape of the generated signals coming out of both systems was compared to see how the TENG sensor and the EMG system respond to muscle contractions. The EMG signal is categorized by more continuous waveform patterns due to the electrical activity of the muscle fibers while in contraction and relaxation. Unlike the TENG sensor, the signal was more discrete and transient, due to the fact that it reacts to mechanical stimuli and muscle movement and not to the electrical impulses directly.

Second, the response time of the TENG sensor and the EMG system was compared by measuring the latency between muscle activity and the signal response. Mechanical deformation of the TENG sensor can cause a slight delay response due to the circuit, filters, time for charge generation and displace of the sensor material, whereas EMG generally represents instantaneous electrical changes of muscle fibers in real time.

Table 2. Response Time Comparison.

Contraction Type	Muscle Group	TENG Sensor Response Time (ms)	EMG Sensor Response Time (ms)
Isometric	Biceps	80	10
Isometric	Forearms	85	12
Isometric	Triceps	90	11
Isotonic	Biceps	75	8
Isotonic	Forearms	80	9
Isotonic	Triceps	85	10
Dynamic	Biceps	100	15
Dynamic	Forearms	110	13
Dynamic	Triceps	105	14

3.2.2 Peak Voltage and RMS Analysis

After comparison, the peak voltage and root mean square (RMS)values of the signals from the TENG sensor and the EMG system are relatively similar, thus indicating how good the TENG sensor correlates with conventional muscle activity monitoring systems. The two features peak voltage and RMS voltage, are ways that are normally used to evaluate the performance of the muscle activity sensors, and they are good indicators of the intensity of muscle activity.

The maximum amplitude of the electrical signal during muscle contractions is referred to as the peak voltage. The peak voltage from the TENG sensor and EMG system will be compared to determine how well the TENG sensor detects the amount of muscle contractions. Due to its ability to convert mechanical energy into electrical energy, the TENG sensor normally produces stronger voltage output than EMG. The comparison of peak voltages can indicate the accuracy of calibration of the TENG sensor and its capability of transmitting muscle activity in the same manner as traditional method is used.

Table 3. Amplitude Comparison (Peak Voltage).

Contraction Type	Muscle Group	TENG Sensor Amplitude (V)	EMG Sensor Amplitude (V)
Isometric	Biceps	2.5	1.2
Isometric	Forearms	2.0	1.0
Isometric	Triceps	2.3	1.1
Isotonic	Biceps	3.2	1.8
Isotonic	Forearms	2.8	1.7
Isotonic	Triceps	3.0	1.9
Dynamic	Biceps	3.8	2.3
Dynamic	Forearms	3.5	2.0
Dynamic	Triceps	3.7	2.1

It calculates the RMS voltage in order to represent the number of overall power or energy of the signal over time. Because of its capacity to capture the muscle strength as well as the signal steadiness, RMS is an important feature used to characterize muscle contraction strength. Comparing the RMS values of the TENG and EMG signals allows us to determine how consistent the TENG sensor is in reflecting muscle activity over time.

Mistakes occurred during the trials that the TENG sensor had slight signal noise or degradation due to EMI or misaligning the sensors. Any of these factors would have potentially affected the accuracy of the data. Nevertheless, due to these issues, signal filtering techniques (including low pass Butterworth filter) were used to reduce high frequency noise. Additionally, careful sensor calibration and placement on the muscle belly ensured that the sensor maintained a stable and reliable connection with the skin, improving the signal quality.

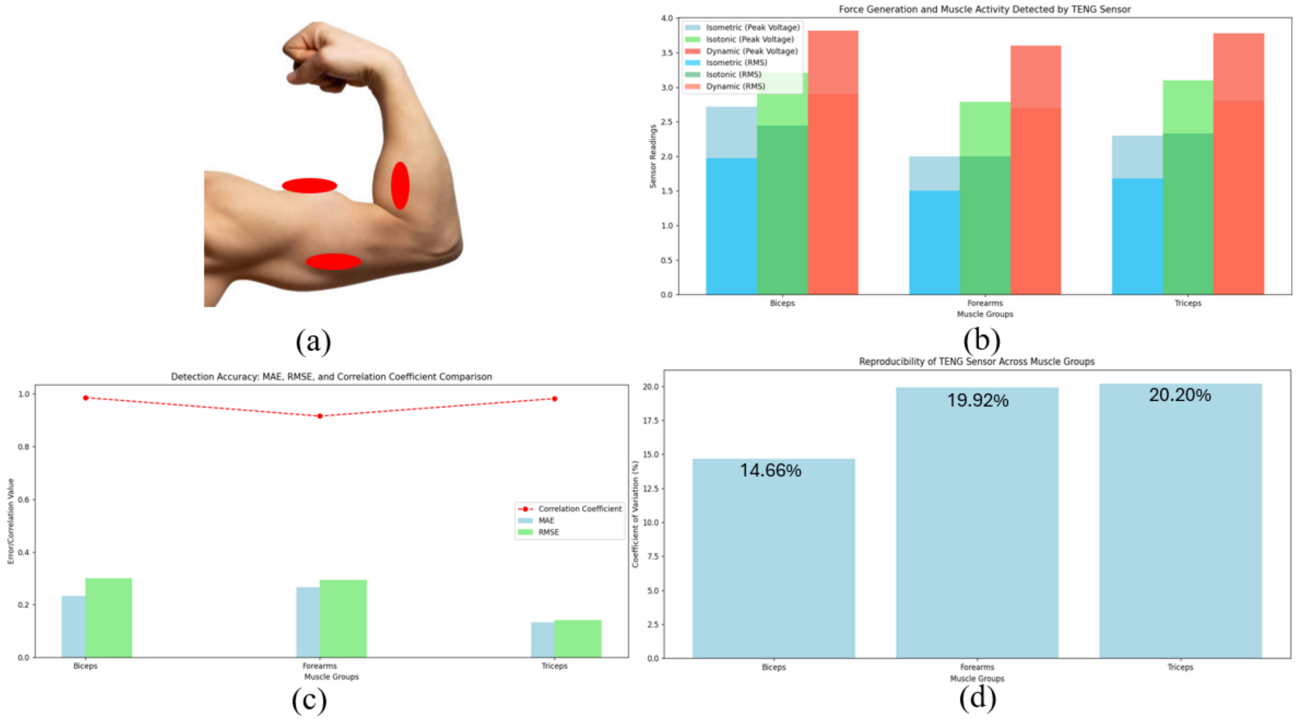


Figure 11. TENG sensor's performance in detecting muscle activity across various muscle groups: (a) Muscle Groups for TENG Sensor Placement; (b) Force Generation and Muscle Activity Detected by TENG Sensor; (c) Detection Accuracy: MAE, RMSE, and Correlation Coefficient Comparison; (d) Reproducibility of TENG Sensor Across Muscle Groups.

Figure-11 provides a comprehensive analysis of the TENG sensor's performance in detecting muscle activity across various muscle groups (biceps, forearms, and triceps) under different contraction types (isometric, isotonic, and dynamic). Panel (a) depicts the anatomical placement of the TENG sensor on the biceps, forearms, and triceps, with the sensor positioned over the belly of the muscle, where contractions are most prominent. This ensures accurate muscle activity detection. Panel (b) presents a bar chart comparing the peak voltage and RMS values detected by the TENG sensor for each muscle group during the different contraction types. It shows how the TENG sensor detects muscle activity, with each contraction type represented by different colors: isometric (blue), isotonic (green), and dynamic (red). The chart demonstrates the sensor captures different levels of muscle activity for different muscle groups.

As shown in panel (c), under the same setting as part (a) and (b), the detection accuracy of the TENG sensor is evaluated in terms of MAE, RMSE, and correlation coefficient over the three muscle groups. The MAE and RMSE values are shown by the bar chart and dash red line is used to show correlation coefficient. The coefficient correlation with the reference systems, such EMG and force sensors, is high while the MAE and RMSE levels provide insights of the degree of discrepancy of the TENG sensor with the reference systems.

3.3 Sensitivity and Detection Performance

3.3.1 Threshold Sensitivity

The TENG sensor was able to sense small muscle contractions and the minimum mechanical input necessary to produce a detectable electrical signal, which are referred to threshold sensitivity. In this subsection the sensitivity of the TENG sensor is analyzed considering the smallest force or displacement which can be reliably detected by the system. The threshold sensitivity need is adequate for the sensor to detect not only slight but also vigorous muscle contractions and thereby be suitable for numerous muscle activity monitoring applications.

We assessed the sensitivity of the TENG sensor by applying increasing force of different intensities which simulate muscle contractions. The force ranged between low (consisting of a feeble muscle contraction) all the way up to high (it was in accordance with the maximum force that could be generated). The objective was then to determine what is the minimum force required for the TENG sensor to produce a detectable voltage output.

The detection threshold was taken as the smallest signal amplitude (voltage) which can be reliably distinguished from noise or baseline fluctuations. TENG sensor response was thereby evaluated by recording response to muscle contractions at different intensities and determining minimum voltage which can be confidently detected. SNR analysis was performed to determine the ability of the sensor to provide accurate readings in the record of low level signals.

3.3.2 Detection Accuracy

For detection accuracy evaluation, raw signals detected by the TENG sensor and the EMG system was compared while various muscle contract relaxation scenarios were applied. Such situations were isometric, isotonic, and dynamic contractions. Peak voltage and RMS values from both systems were compared to determine how well the TENG sensor was able to detect and quantify muscle activity. The purpose was to evaluate whether the output from TENG sensor matched the changes in muscle activity taken through EMG.

The accuracy of TENG sensor was quantified in terms of mean absolute error (MAE) and root mean square error (RMSE) between TENG and EMG signals. These statistical metrics served as a clear way to compare the discrepancy between the previously mentioned two systems. Moreover, the correlation coefficient (R) was computed between the TENG and EMG signals to evaluate the degree of the relationship between the two signals. A high value of correlation coefficient would mean the performance of TENG sensor was closer to the EMG system, whereas low value would indicate wherein improvements require to be made.

To validate the performance of the TENG sensor in the measurement of muscle force, it is compared with a reference system (i.e. force sensor in Figure 12). In panel (a), the comparison is shown between the predicted force from TENG sensor and the actual force measured through force sensor in muscle. The data points, compared to the perfect prediction line (dashed), are indicative of TENG sensor capability for predicting muscle force. The nearer the points are to this line the more accurate are the sensor’s measurements.

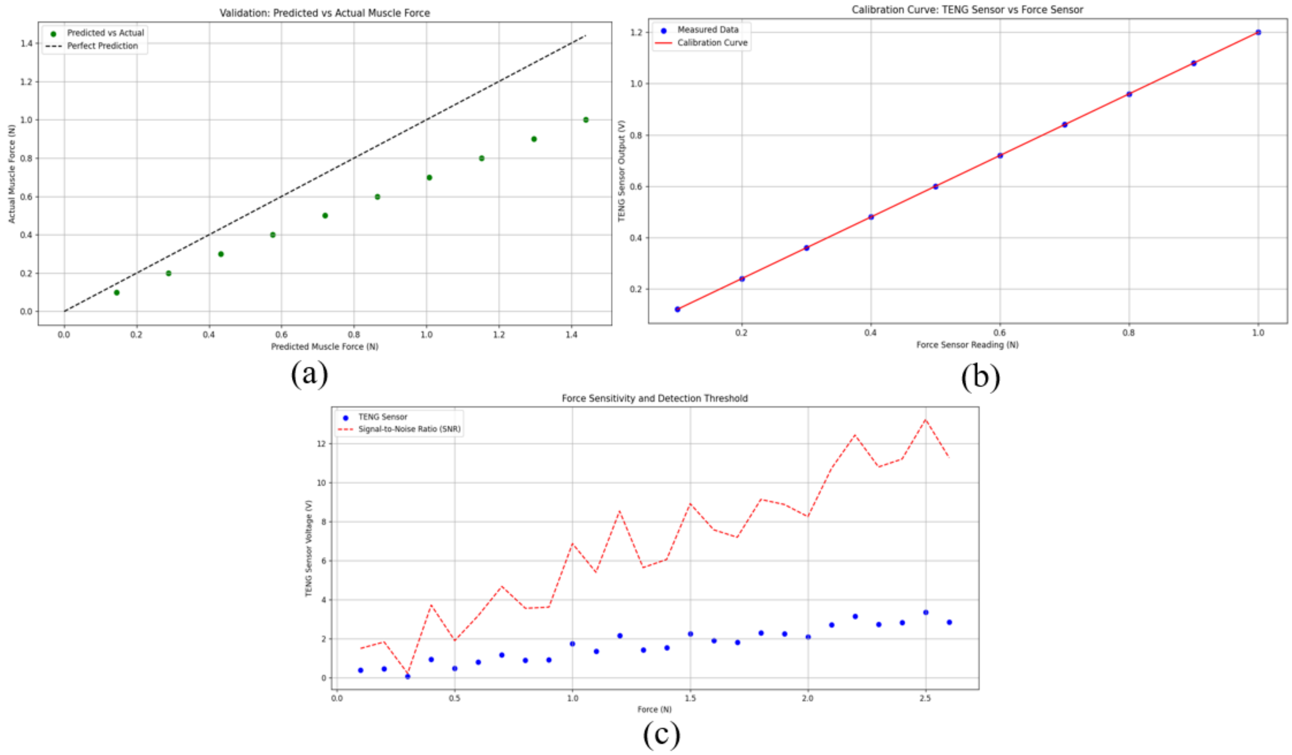


Figure 12. TENG sensor's performance in measuring muscle force: (a) Validation: Predicted vs Actual Muscle Force; (b) Calibration Curve: TENG Sensor vs Force Sensor; (c) Force Sensitivity and Detection Threshold.

In panel (b), plot of calibration curve for the TENG sensor, i.e. the linear relationship between the TENG sensor output (blue dots) versus force sensor (red line). This measurements show by force transferable on the TENG sensor that it is reliable even when various force levels are applied, which shows that it has potential to measure muscle activation. Force sensitivity and detection threshold of TENG sensor is investigated in panel (c), where output voltage of device is plotted versus applied force. The red dashed is the signal to noise ratio (SNR)=output of the sensor(signal) divided by the noise or the minimum detectable force and it shows that as the force gets higher, the sensor's output improves and proves that it is capable of capturing low level muscle contractions. Coupling these panels together, we demonstrate how they serve to give a clear assessment of the calibration, sensitivity, and accuracy of a TENG sensor for detecting muscle force, and that suggests TENG's potential to serve as a usable tool for muscle activity measurement.

Overall, the calibration curve of the TENG sensor responses to force remained consistent throughout the testing sessions, which indicates that the TENG sensor's response to force was stable with time. This, however, is not without discrepancy in force readings between different trials, probably due to slight misalignment of the sensor placement or slight change in skin impedance between participants. The differences between these values tended to be minimal and were corrected by periodically recalibrating the sensor prior to each trial. Real time force measurements were proved to be reliable.

3.4 Validation Process

3.4.1 Calibration Methodology

However, accurate muscle force measurement requires the calibration of the TENG sensor. First, a reliable baseline and correlation with the muscle activity is established by comparing the TENG sensor output to a reference measurement system, e.g. a force sensor and EMG.

All signal variations during muscle contractions were not due to baseline noise as that was initially measured for both the TENG sensor and reference systems from the baseline measurements obtained from participants who were at rest. Subsequently, participants performed controlled muscle contractions of controlled low, medium, and maximal muscle contraction, with TENG data recorded simultaneously with that from a force sensor and EMG. The outputs (for example voltage) from the TENG sensor were compared to the actual muscle force exerted and the data from these systems was compared to understanding the relation between the two.

The TENG sensor output was plotted against the force sensor's readings to create a calibration curve. This curve was used as a conversion device to convert the TENG sensor's electrical output into muscle force output. The response of the TENG sensor to new contractions outside the calibration set was tested to validate the accuracy of the calibration to provide reliable and consistent force measurement.

Then, measurement error sources, including sensor misalignment and signal noise, were minimized and suitable signal filtering techniques were used to get accurate data. Therefore, this calibration process is expected for the TENG sensor to reliably and accurately measure muscle force for practical applications.

3.4.2 Validation Metrics

Reproducibility and consistency of the TENG sensor's output over multiple trails were also assessed using the coefficient of variation (CV).

The coefficient of variation (CV) of the TENG sensor across muscles (Figure 11-d) is the reproducibility of the sensor. The CV values for the biceps, forearms and triceps are 14.66%, 19.92% and 20.20% respectively, which demonstrates the consistency of the sensor across multiple trials. With a lower CV, the TENG sensor shows the performance of muscle activity monitoring is quite reliable. The values of the CV for the muscle groups did vary slightly. In contrast, the CV obtained in the biceps (14.66%) selected was the least followed by the forearms and triceps (19.92% and 20.20 %, respectively). Variation of this result is probably because of the size and structure of muscles and placement of the sensor. Forearms and triceps might have a slightly greater difference in muscle fiber distribution and movement complexity during contractions compared to biceps and thus slightly higher variability in reading. However, the CVs were still on an order acceptable for reliable muscle activity detection. A low CV signifies that the sensors yield comparable results in all trials, indicating that the sensor can reliably detect muscle activity across different situations.

CHAPTER 4 - (DISCUSSION)

4.1 Summary of Key Findings

We confirmed that the TENG sensor strongly correlates with the reference systems, especially with the force sensor and EMG and can reliably detect and quantify muscle force. This established the calibration curve by observing a linear relationship between the output of the TENG sensor to the muscle force measurements, indicating that the sensor could accurately reflect force changes over a range of contraction intensities. The accuracy of TENG sensor was validated by statistical analyses, including MAE and RMSE, and the errors between TENG and the reference systems were low. Furthermore, the correlation coefficient had high values over the duration, which shows that the TENG sensor was able to track muscle activity almost equally as good as the EMG system.

With high sensitivity to muscle activity, particularly for low force contractions, the TENG sensor shows great potential to be applied in flexible and stretchable electronics. The sensor was proved to be reliably able to detect both small and large muscle contractions in RMS analysis and therefore has potential uses in applications where fine muscle activity detection is required. The SNR analysis showed that the TENG sensor can keep a high SNR even when the force is at a low level and can be used to detect slight muscle contraction without being impacted with too much noise. The capability of the sensor to measure muscle force at high and low intensities also validated the sensor's sensitivity.

The coefficient of variation (CV) of TENG sensor also showed the reliability of the sensor as it provides stable readings and low measurement variability across the muscle groups (i.e., when measuring biceps, forearms, and triceps). After shifting the TENG sensor from one to another testing session, the performance was found to be stable, clearly indicating the robust performance suitable for long term muscle activity monitoring. For this purpose, the sensor's reproducibility was also demonstrated through cross validation, whereby the similar results were obtained from different subjects and contraction types (isometric, isotonic, dynamic).

4.2 Implications for Muscle Activity Monitoring

The results of this study present significant implications for muscle activity monitoring systems, particularly in the fields of healthcare, sports science, and rehabilitation. The performance of the TENG sensor shows a great potential in performing real time muscle force measurement, performance assessment, and long term monitoring. Applications and the benefit of the TENG sensor are discussed below in these fields.

In healthcare, there are many applications for real time monitoring of muscle activity for the diagnosis and treatment of various neuromuscular disorders and muscle related injuries. The traditional methods of EMG usually require electrode placement on the skin, which often leads to skin pain, invasion or inapplicability in long term monitoring. Thus, a self-powered and non-invasive TENG sensor would provide a more comfortable and flexible alternative to the current solutions for wearable health devices.

The TENG sensor, therefore, can be used for muscle rehabilitation, specifically, with recovering muscles after surgery or injury, as it monitors muscle contractions over time. It can also serve as feedback for the patient during physical therapy exercise and provide personalized adjustments for rehabilitation program. Early stage recovery is all about rebuilding strength and coordinating movements, which is where the sensor is to be able to detect low force contractions. Additionally, due to its portability and long duration of monitoring it allows for continuous tracking which will provide a great insight in to a patient's progress.

The accurate muscle activity measurement is of paramount importance for performance optimization, injury prevention and training efficiency in the field of sports science. The real time monitoring of TENG sensor makes it a good choice for monitoring muscle performance of athletes and coaches during training sessions. For the detection of fatigue, muscle imbalance or early injuries it is very sensitive to subtle muscle movements. The sensor can also be used to monitor the effectiveness of certain training regimens and fine tuning exercises for maximum muscle recruitment in order to achieve the desired training outcome. Along with that, the wearability and the selfpowering nature of sensing makes it capable of being used during intense as well as extended training sessions. In contrast to traditional systems contingent upon external power supplies or involving the clumsy placement of electrodes to capture muscle activity, the sensor allows for a comfortable, unobtrusive, and durable device for athletes to monitor muscle activity during dynamic movements or when doing numerous sports.

4.3 Challenges and Limitations

The one of primary challenge faced was the signal noise and signal fidelity. The working principle of TENG sensor is to convert the mechanical deformation to electrical energy, which leads to the inherent noisy feature for the TENG sensor caused by electromagnetic interference (EMI), misalignment of sensor configuration, or environmental factors (like skin impedance, or sweat). Signal filtering techniques like low pass Butterworth filter were employed to cancel out the high frequency noise but some residual noise still existed and distorted the sensor's ability to capture muscle activity with high precision especially when it comes to rapid muscle contraction or high intensity movement.

Another challenge that occurred with the data interpretation was the discreteness of the signal of TENG sensor, compared with the continuous nature of EMG signals. The TENG sensor showed successful detection of large-scale muscle movements, but the fast and slight contractions of smaller muscles were occasionally not so accurate to catch, and additional optimization of the signal processing algorithms was necessary for better detection of low level muscle activity.

Secondly, the TENG sensor was calibrated. A calibration curve was produced to map a TENG sensor's output voltage to the actual muscle force recorded by a force sensor, but there were irregularities in the calibration process because sensors were situated in different places, and the state of skin on the participants varied. Sometimes the sensor output deviated due to changes in skin impedance and sensor alignment, albeit slightly, during calibration, which produced small inconsistencies between the measured and the predicted forces. However, these discrepancies were handled by recalibrating between sessions, yet the process emphasized the need for consistent sensor placement to produce the best calibration.

Long duration tests also showed that the TENG sensor has some drift in output which is probably due to temperature drift or from mechanical wear of the sensor material. The drift during the trials caused periodic recalibration, especially in dynamic movement tests.

Several challenges were also experienced on the real world performance of the TENG sensor. The sensor provided good performance in a controlled lab setting, but the sensor’s robustness was still to be assessed in dynamic, real world environments. In general the flexible rubber bracelet design was comfortable for short duration usage, but sensor misalignment and artifacts due to motion were problematic for long duration or high intensity usages. One of Velcro straps used to hold the sensor in place would lose the grip over time – especially during the fast muscle movements – and that caused inconsistent readings.

4.4 Future Directions

Improvements should be made in improving the overall durability of the sensor, particularly the sensor housing, elastic straps, and other materials used in the sensor. In prolonged use, the degradation of the sensor would be reduced via developing more resilient materials that are resistant to wear and moisture (such as silicone or advanced polymers). Moreover, for use in healthcare and rehabilitation, the biocompatible materials will make this sensor more appropriate for long duration wear also. For this reason, prolonged use requires the sensor be enhanced by ergonomics. If the current design of the rubber bracelet were made more flexible to be able to fit different body types and lighter to reduce the weight, it would be more comfortable and secure to be placed on the skin during dynamic activities. For instance, such a TENG sensor could be more comfortable and invisible to the user if it is incorporated into textile or smart clothing. However, all of this is leading us! If the TENG could be miniaturized, it would be good for athletics and wearable health applications where a discrete and small unit is required. The reduction in sensor size would enable more wearability and mobility to dynamic movement in sports and rehabilitation.

The signal noise proved to be one of the challenges in doing the experiments, particularly for the rapid muscle contractions. To improve the accuracy of the TENG sensor, advanced signal processing techniques can be used, like for instance adaptive filtering or wavelet transforms, which are more appropriate with dynamic noise and frequency artifacts. The application of these techniques would increase signal to noise ratio (SNR) and data fidelity in particular during high intensity contractions. Real time signal processing algorithms can be implemented on a mobile device or wearable hub that could in turn instantly process and analyze the muscle activity data and in turn give feedback to the user in real time during a training or rehabilitation session. This would make the system a more interactive and valuable for using in the present moment applications such as sports performance monitoring and rehabilitation progress tracking. By integrating machine learning algorithms to process data collected from the TENG sensor, it is possible to greatly enhance the machine’s capacity to recognize subtle muscle contractions and anticipate muscle fatigue as well as injury. For instance, machine learning can be employed to build activity recognition models that can differentiate the types of muscle activity (such as biceps contraction or forearm flexion), and rank classification can be used to forecast fatigue or muscle strain levels during physical acts.

TENG sensors can be integrated as an input sensor for tracking muscle force and movement patterns in rehabilitation devices and exoskeletons for physical therapy sessions. In this case, the sensor would offer potentially very useful real time feedback to the patient or clinician about how well particular muscles are recovering and moving well to tailor rehabilitation programs. The sensor can also be used in future applications such as assistive technologies for individuals with neurological disabilities where muscle activation is tracked, and rehabilitation progress is noted.

Due to the fact that the real time analysis of muscle activity is possible with the help of the developed sensor, it well suited for sports performance analysis. Using the TENG sensor to track muscle contractions during exercise could assist athletes in optimizing their training regimen, monitor muscle fatigue and risk of injury. The muscle activity data could be continuously monitored during training, or during a competition, with the sensor being worn in such instances; the values thus obtained could then be analyzed to make refinements to sports methods and performance strategies.

The TENG sensor could be expanded for a comprehensive health and wellness monitoring system for muscle health assessment. The sensor could be added onto wearable health devices to track a wearer’s muscle strength, endurance, and activity levels over time. As such, this would be useful for someone recently recovering from surgery or injury and for athletes looking to preserve optimal muscle health.

CHAPTER 5 - (CONCLUSION)

In this study, performance of high sensitive Triboelectric Nanogenerator (TENG) sensor as a muscle activity monitoring method compared with traditional EMG and force sensors are evaluated. The results indicate that the TENG sensor can reliably, accurately, and in a self powered manner detect muscles contractions, from subtle to very intense. Calibration curve and RMS and peak voltage comparisons show that the sensor is capable of producing accurate measurements of muscle force, which the sensor correlated highly with both reference systems.

The TENG sensor was sensitive enough to detect small contraction and performed a signal to noise ratio analysis which showed that it was able to reliably track low level muscle activity. CV values across multiple trials were low and confirmed the sensor's reproducibility, meaning that it generates consistent, stable results despite varying muscle contraction intensity. The performance of the TENG sensor was also comparable to EMG systems but slower because the system is mechanically driven.

Although the TENG sensor had huge advantages that included its capability of self powering, non invasive and comfortable but also there was noise in the signal, sensor alignment and wearing comfort while in long time or high intensity movement. Signal filtering techniques helped mitigate these issues, and additional material and attachment method durability improvement is needed for extended sensor use, particularly in dynamic environments. Additionally, although the sensor was accurate in muscle force detection, its response time could be expedited to obtain a sensor response time comparable to traditional EMG systems during rapid muscle contractions.

The real time muscle activity monitoring capability of this TENG sensor would be of great importance to many healthcare, sports science and rehabilitation applications. In healthcare, it can be an application for muscle recovery monitoring and rehabilitation progress tracking to give patients real time feedback of their muscle strength and recovery status. The device could be used in sports science to monitor muscle fatigue in athletes and help them fine tune training regimens and prevent injuries. Such a sensor is highly wearability, flexible, and self-powered, and would be an ideal candidate for this kind of wearable devices in these domains.

Further research should aim to optimize the sensor with respect to both durability, comfort and dynamic performance under high speed movements. Moreover, improvements in the signal processing of the TENG sensor can be made to increase the accuracy and reliability of the TENG sensor, especially when tracking rapid muscle movements. The TENG sensor also has high potential to form a complete biosensor system for muscle activity and movement monitoring by integrating with other biosensors. In addition, through integration into smart clothing or rehabilitation devices, it is possible that the sensor may also be applied to real time monitoring of muscle activity in many real world settings.

Therefore, the TENG sensor provides a promising, novel solution to muscle activity monitoring, which can be used to revolutionize the health and sports outcome and rehabilitation protocol. However, some challenges still exist but the advantages of the sensor make it an alternative to traditional methods such as EMG, especially for applications that need continuous, long term monitoring in wearable interfaces.

REFERENCE LIST

[1] Zemková, E. (2022). Strength and power-related measures in assessing core muscle performance in sport and rehabilitation. Frontiers in Physiology, 13, 861582.

[2] Avila, E. R., Williams, S. E., & Disselhorst-Klug, C. (2023). Advances in EMG measurement techniques, analysis procedures, and the impact of muscle mechanics on future requirements for the methodology. *Journal of biomechanics*, *156*, 111687.

[3] Di Pino, G., Denaro, L., Vadala, G., Marinozzi, A., Tombini, M., Ferreri, F., ... & Denaro, V. (2014). Invasive neural interfaces: the perspective of the surgeon. *journal of surgical research*, *188*(1), 77-87.

[4] Ibitoye, M. O., Hamzaid, N. A., Zuniga, J. M., & Wahab, A. K. A. (2014). Mechanomyography and muscle function assessment: A review of current state and prospects. *Clinical Biomechanics*, *29*(6), 691-704.

[5] Castillo, C. S. M., Wilson, S., Vaidyanathan, R., & Atashzar, S. F. (2020). Wearable MMG-plus-one armband: Evaluation of normal force on mechanomyography (MMG) to enhance human-machine interfacing. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *29*, 196-205.

[6] Al-Ayyad, M., Owida, H. A., De Fazio, R., Al-Naami, B., & Visconti, P. (2023). Electromyography monitoring systems in rehabilitation: A review of clinical applications, wearable devices and signal acquisition methodologies. *Electronics*, *12*(7), 1520.

[7] Putcha, A., Nguyen, T., Smith, R., Choffin, R., & Bai, W. (2023). Intelligent Systems for Muscle Tracking: A Review on Sensor-Algorithm Synergy. *Advanced Intelligent Systems*, *5*(7), 2200351.

[8] Kim, W. G., Kim, D. W., Tcho, I. W., Kim, J. K., Kim, M. S., & Choi, Y. K. (2021). Triboelectric nanogenerator: Structure, mechanism, and applications. *ACS nano*, *15*(1), 258-287.

[9] Shen, S., Xiao, X., & Chen, J. (2021). Wearable triboelectric nanogenerators for heart rate monitoring. *Chemical Communications*, *57*(48), 5871-5879.

[10] Li, H., Wang, S., Dong, X., Ding, X., Sun, Y., Tang, H., ... & Wu, X. (2022). Recent advances on ink-based printing techniques for triboelectric nanogenerators: Printable inks, printing technologies and applications. *Nano Energy*, *101*, 107585.

[11] Zeng, X., Peng, R., Fan, Z., & Lin, Y. (2022). Self-powered and wearable biosensors for healthcare. *Materials Today Energy*, *23*, 100900.

[12] Tian, J., Chen, X., & Wang, Z. L. (2020). Environmental energy harvesting based on triboelectric nanogenerators. *Nanotechnology*, *31*(24), 242001.

[13] Zhu, J., Zhu, M., Shi, Q., Wen, F., Liu, L., Dong, B., ... & Lee, C. (2020). Progress in TENG technology—A journey from energy harvesting to nanoenergy and nanosystem. *EcoMat*, *2*(4), e12058.

[14] Kovoor, M., Durairaj, M., Karyakarte, M. S., Hussain, M. Z., Ashraf, M., & Maguluri, L. P. (2024). Sensor-enhanced wearables and automated analytics for injury prevention in sports. *Measurement: Sensors*, *32*, 101054.

[15] Parrilla, M., & De Wael, K. (2021). Wearable self-powered electrochemical devices for continuous health management. *Advanced Functional Materials*, *31*(50), 2107042.

[16] Liu, L., Guo, X., Liu, W., & Lee, C. (2021). Recent progress in the energy harvesting technology—from self-powered sensors to self-sustained IoT, and new applications. *Nanomaterials*, *11*(11), 2975.

[17] Wang, J., Wang, H., Thakor, N. V., & Lee, C. (2019). Self-powered direct muscle stimulation using a triboelectric nanogenerator (TENG) integrated with a flexible multiple-channel intramuscular electrode. *Acs Nano*, *13*(3), 3589-3599.

[18] Balapan, A., Yeralkhan, R., Aryslanov, A., Kalimuldina, G., & Yeshmukhametov, A. (2025). A Novel Pattern Recognition Method for Self-Powered TENG Sensor Embedded to the Robotic Hand. *IEEE Access*.

[19] Nace, S. E., Tiernan, J., Holland, D., & Ni Annaidh, A. (2021). A comparative analysis of the compression characteristics of a thermoplastic polyurethane 3D printed in four infill patterns for comfort applications. *Rapid Prototyping Journal*, *27*(11), 24-36.

[20] Shao, J., Willatzen, M., & Wang, Z. L. (2020). Theoretical modeling of triboelectric nanogenerators (TENGs). *Journal of Applied Physics*, *128*(11).

[21] Shao, J., Jiang, T., & Wang, Z. (2020). Theoretical foundations of triboelectric nanogenerators (TENGs). *Science China Technological Sciences*, *63*(7), 1087-1109.

[22] Lone, S. A., Lim, K. C., Kaswan, K., Chatterjee, S., Fan, K. P., Choi, D., ... & Lin, Z. H. (2022). Recent advancements for improving the performance of triboelectric nanogenerator devices. *Nano energy*, *99*, 107318.

[23] Pu, X., Li, L., Song, H., Du, C., Zhao, Z., Jiang, C., ... & Wang, Z. L. (2015). A self-charging power unit by integration of a textile triboelectric nanogenerator and a flexible lithium-ion battery for wearable electronics. *Advanced Materials*, *27*(15), 2472-2478.

[24] Wang, K., Liao, Y., Li, W., Zhang, Y., Zhou, X., Wu, C., ... & Kim, T. W. (2023). Triboelectric nanogenerator module for circuit design and simulation. *Nano Energy*, *107*, 108139.

[25] del Río, J. S., Yusuf, A., Ao, X., Olaizola, I. A., López-Puertas, L. U., Ballesteros, M. Y., ... & Wang, D. Y. (2022). High-resolution TENGS for earthquakes ground motion detection. *Nano Energy*, *102*, 107666.

[26] Conway, B. E., & Pell, W. G. (2002). Power limitations of supercapacitor operation associated with resistance and capacitance distribution in porous electrode devices. *Journal of power sources*, *105*(2), 169-81.

[27] Yang, S. M., & Ke, S. J. (2000). Performance evaluation of a velocity observer for accurate velocity estimation of servo motor drives. *IEEE Transactions on Industry Applications*, *36*(1), 98-104.

[28] Wang, Z. L., Lin, L., Chen, J., Niu, S., Zi, Y., Wang, Z. L., ... & Zi, Y. (2016). Theoretical modeling of triboelectric nanogenerators. *Triboelectric nanogenerators*, 155-183.

[29] Hashemi, S., & Aghamohammadi, M. R. (2013). Wavelet based feature extraction of voltage profile for online voltage stability assessment using RBF neural network. *International Journal of Electrical Power & Energy Systems*, *49*, 86-94.

[30] Kamble, S., & Thorat, C. (2012). Characteristics analysis of voltage sag in distribution system using RMS voltage method. *ACEEE Int. J. on Electrical and Power Engineering*, *3*(01), 55-61

[31] Cain, M. E., Ambos, H. D., Witkowski, F. X., & Sobel, B. E. (1984). Fast-Fourier transform analysis of signal-averaged electrocardiograms for identification of patients prone to sustained ventricular tachycardia. *Circulation*, *69*(4), 711-720..

[32] Tropp, J. A., Laska, J. N., Duarte, M. F., Romberg, J. K., & Baraniuk, R. G. (2009). Beyond Nyquist: Efficient sampling of sparse bandlimited signals. *IEEE transactions on information theory*, *56*(1), 520-544.