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MuscleDrive: A Proof of Concept Describing the Electromyographic Navigation of a Vehicle

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Abstract: This paper describes a device that enables a human to interact with a vehicle without using one's hands. The device that we propose acquires the surface electromyogram signal of the muscles of the forearm that allow the flexion and extension of the fingers and the palm. We call this device MuscleDrive. MuscleDrive can classify flexion and extension motions of the hand and their intensity. The strength of flexion or extension exerted by the user can be estimated by analyzing the electromyogram. Motions of different intensities can be used as unique input signals that would perform distinct functions about manipulating a vehicle without any obvious movement of the upper arm, as is the case with isometric contraction of the biceps or the triceps that is used to create motion in the forearm. Using the strength of muscle contraction as a measure of intensity, the user can propel a vehicle forward, apply brakes to it, reverse it, and make it turn. An algorithm to map the electromyogram signal to the desired input has been developed and explained in this paper. The results show that the device can allow a user to navigate a vehicle without explicitly using the palm, the fingers, or the upper arm. The neural signal from the user's brain that enables the user to make motions in the palm alone can be used to control a vehicle.

Keywords: Electromyography; Human-Computer Interface; Myoelectric Activity; Navigation of a Vehicle; MuscleDrive; Needle Electromyography; Guillain-Barre Syndrome; Microprocessors and Microcontrollers.

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1. Introduction

Fitness and health are considered some of the most treasured possessions of humans. Diseases like gangrene injuries that may occur during an accident and certain chronic diseases may lead to conditions where certain body parts, particularly limbs, may become non-functional, may be entirely lost, or may need to be amputated for overall benefit and increase in longevity of the patient. Such instances are often the cause of agony, dependence on others, weakness, and depression [1]. Current innovations in science and technology have led to the invention and development of advanced prosthetics, which offer hope for victims of paralysis, accidents, and amputation [1]. Technologies like Functional Electrical Stimulation are being used for patients who have become paralyzed, especially due to neural injury in the spinal cord [2]. However, the costs of providing prosthetics and Functional Electrical Stimulation [3] to those who need them and can benefit from them can still be high and may be unaffordable for the common populace. Therefore, alternatives to such devices and technologies are being actively researched. Human-Computer Interface (HCI) [4] is one such area of research, and within its ambit lies the use of bio-acquisition systems [5]. These systems incorporate the use of biologically generated electrical signals like Electroencephalogram,

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Electrocardiogram, or Electromyogram (EMG) as input [5, 6], employing which they provide the desired output that can then be used to overcome the limitations imposed on them by a patient's disease or injury [1].

1.1. Electromyography

Electromyography (EMG) is a technique to measure a muscle's reaction in response to a neural stimulus [6, 7]. It discerns the action potential, also termed myoelectric activity, generated in a muscle cell known as myocyte, estimating the electrical potential generated in a muscle when it contracts [8]. It analyses the extent of neural activation of a muscular component. A motor unit consists of a motor neuron and the entirety of muscle fibres that it supplies to [9]. In conventional electromyography, also known as intramuscular myography [10, 11], disposable concentric needle electrodes are introduced into muscles [6]. Needle electromyography, also known as fine wire electromyography, is another name for intramuscular myography [12].

In needle electromyography, a disposable concentric needle electrode is used, and a fine wire passes through the axis of the needle [6]. Myographic information is carried from the electrode to the microprocessor for conversion to waveforms. Exploration of waveforms generated by the electrical activity of a muscle and the number of spikes per unit time of a single motor unit or multiple motor units within a muscle constitutes an important part of electromyography, surface as well as intramuscular [6, 7].

Figure 1: Needle Electromyography [13]

In surface electromyography, electrodes do not need to penetrate the skin [12]. They are attached to the skin using adhesive pads. In this way, it is a non-invasive technique. BIOPAC MP36 data acquisition system uses surface electromyography. Measurement of EMG is more easily performed on muscles closer to the skin. EMG cannot circumvent the action potentials of muscles on the periphery and discern those of deeper muscles [14].

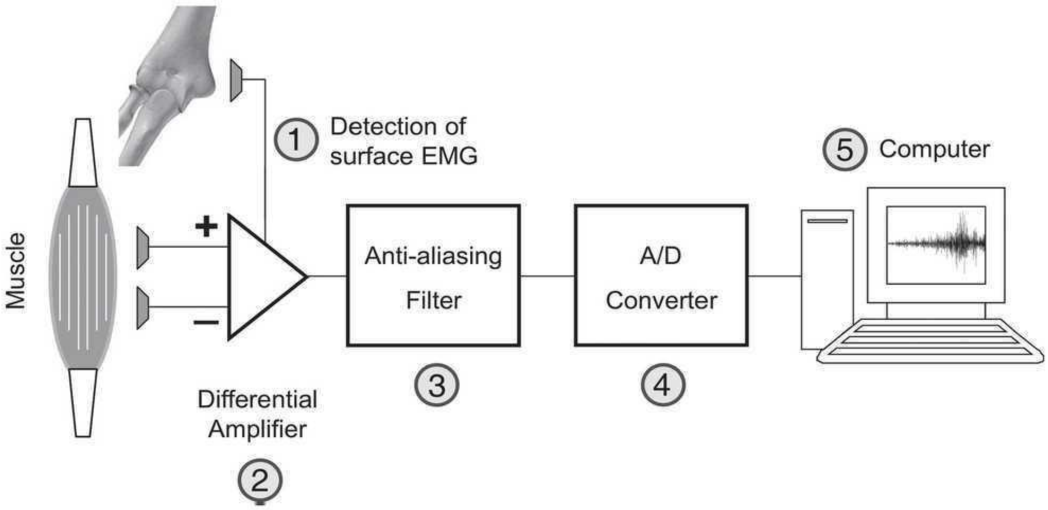

Figure 2: Block diagram of how a surface electromyogram is acquired. It is a non-invasive technique [15]

The chief steps of acquiring surface electromyograms, as shown schematically in Figures 1 and 2, are detecting myoelectric potentials with surface electrodes and a reference electrode, illustrated here as placed on the medial epicondyle of the humerus. All electrodes use adhesive pads; 2. the amplification of such potentials with differential amplifiers, which, in the case of BIOPAC MP36 system, is performed within the data acquisition unit as an inbuilt functionality; 3. analogue filtering of the amplified potentials to avoid aliasing. This occurs within the data acquisition unit as an inbuilt functionality in the BIOPAC MP36 system; 4. the sampling of the surface electromyogram into digital voltage. This is also done internally in the BIOPAC MP36 data acquisition unit. 5. The values are then taken to and stored on a computer.

1.2. Human-Computer Interface

Human-computer interaction (HCI) is the junction of human physiology and computer engineering. This field involves the development of user-interface tools. The scientists in this field focus on expanding automation through enhancing, easing, and technologically augmenting the interaction between humans and the non-living world. Through this, they focus on increasingly better satisfaction of human needs [4].

In the wake of the emergence of the World Wide Web and the proliferation of cellular telephony, voice-recognition and translation systems, sensors, and mechatronics, computer technology has assumed a ubiquitous and all-powerful role. The growth in human technological competence has closely shaped the interactions between man and machine. This led to the rise of a need to forge devices that are made to render these interactions more akin to human experience. This widened the discipline of Human-Computer Interaction (HCI), appending varied fields such as cognitive science, natural language processing, identification of emotion, neurophysiology, etc. within its territory.

The arena of HCI is dedicated to the conception, execution, and assessment of human-technological interfaces that facilitate user experiences through computer engineering. This encompasses user interface design, user-centred design, and user experience design [16]. According to Kanade [16], the most important constituents of HCI are the user, the goal to be achieved, the type and design of the human interface, and the need to adapt the designed system to various environments.

In the context of our study, HCI is used to build a system for real-time measurement of human physiological signals and to use unconventional physiological signals to perform conventional interactions with technologies and the non-living world. Our project will prove to be helpful to people suffering from chronic conditions like hemiplegia (which itself can result from a stroke), loss of extremities or extremity function in an accident, and disorders like amyotrophic lateral sclerosis (ALS) and Guillain-Barre Syndrome [1]. Our project aims to afford an alternative ability to individuals with motor and neurological incapacity. Widespread advancements in the development of the Internet of Things, microprocessors, and microcontrollers have enabled us to bring specially-abled humans to par with others.

2. Background and Related Work

We conducted systematic background research to understand how HCI systems can aid specially-abled humans in living a more fulfilling and independent life. The study by Saboo et al. [1] used electrooculogram signals to control bionic limbs, prosthetics, and robotic arms. They have used the BIOPAC MP36 data acquisition system for their study. Genoud et al. [17] have exemplified using electromyographic (myoelectric) signals to control a remote-controlled vehicle.

Andreasen and Gabbert [18] have demonstrated the navigation of a power wheelchair using an electromyographic switch. Park and Kim [19] have designed a human-computer interface device developed to play a fighting action game. They have named it 'Muscleman.' de Freitas et al. [20] have built a prototype designed to direct the functionalities in a vehicle through gestures captured by myoelectric signals. Hunter et al. [21] have presented their unique design of an electromyography-controlled vehicle using DE0 Nano.

Our work does not rely on hardware platforms like Arduino or Raspberry Pi. It primarily relies on programming and software integration to connect the EMG and the remote-controlled vehicle seamlessly. This makes it different from the projects and studies perused to gain contextual insight into the undertaken task.

3. Theoretical Approach

For the difference in myoelectric signal from minute changes in gestures to be perceived by the system, feature extraction from the EMG must be sensitive and accurate. For this, we need to capture significant information from the myoelectric signal. To do that, EMG waveforms must be processed. This enhances their quality and allows for extracting relevant features for further analysis. Processing techniques involve signal processing methods, feature extraction, and machine learning approaches. EMG signals are contaminated with noise, comprising power-line interference and movement artifacts. High-pass, low-pass, and band-pass filters remove unwanted frequency components and isolate the EMG signal of interest.

Rectification and wavelet denoising must suppress noise while preserving important signal characteristics. Using neural networks such as autoencoders and deep denoising networks can remove noise from the EMG data. Normalization is also needed because EMG signals are of varying amplitude. Differential electrode placement and muscle contraction strength cause variations in EMG waveform recordings. Baseline correction must be applied to standardize the amplitude range across different recordings, making them more comparable.

Information about signal distribution across frequency bands must be captured to increase system sensitivity to various gestures. Convolutional Neural Networks (CNNs) extract relevant features and learn discriminative representations from the EMG data. EMG recordings contain artefacts caused by electrode movement, electrode-skin impedance changes, and, rarely, external interference. The implementation of CNNs should remove them (Fig.3).

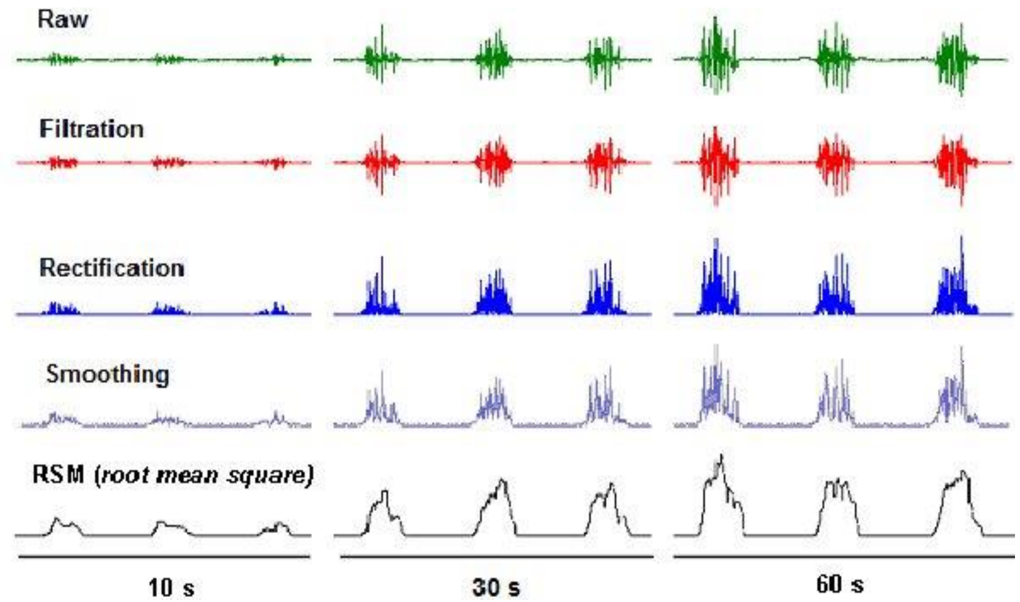

Figure 3: An instance of how EMG signals are preprocessed [22]

We used a pre-trained InceptionV3 model, which is a CNN, to classify EMG waveforms based on different tasks. CNNs were trained to classify EMG signals into different muscle actions and to detect specific motor patterns. Therefore, by combining signal processing techniques with machine learning approaches, EMG waveform preprocessing enhanced the quality of our data, helped us extract relevant features, and enabled subsequent analysis and interpretation (Fig.4).

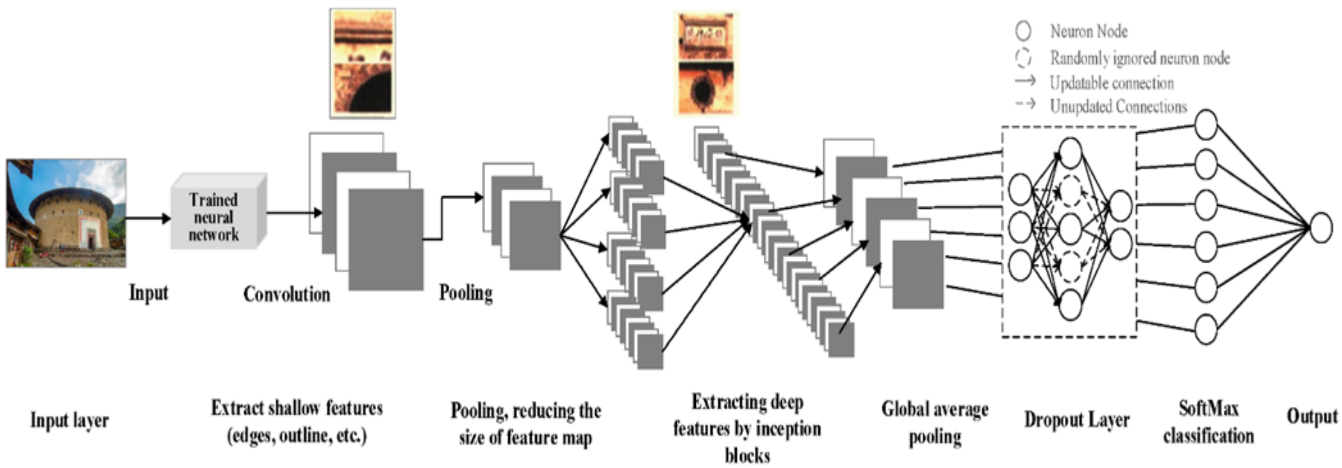

Figure 4: An example of an InceptionV3 Model [23]

4. Methods

We intend to manage a remote-controlled car [24] using surface EMG [25]. This was implemented with the BIOPAC MP36 data acquisition system, which acquires the electromyographic (EMG) data from a human arm. The BIOPAC MP36 data acquisition system, included in the BIOPAC Student Lab package, is an embedded system with a microprocessor [26]. We used the Moorebot Scout as the remote-controlled vehicle (Fig.5).

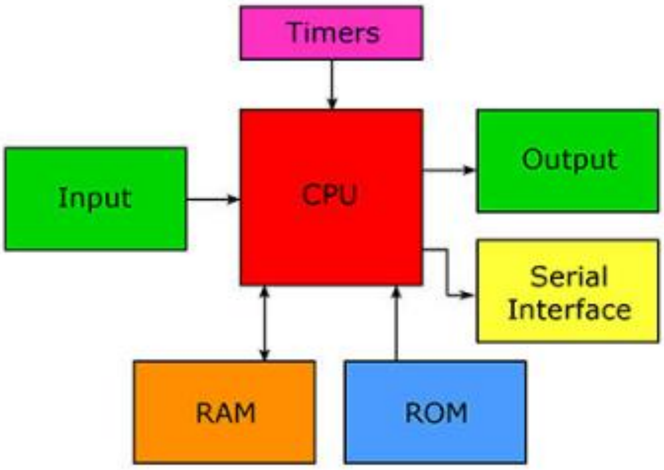

Figure 5: A block diagram of a microprocessor [26]

The MP36 data acquisition system's microprocessor uses the RAM and ROM of its connected computer. It uses a serial input to measure the electrical activity in the muscles, accepts it as an incoming signal, and processes it to convert it into a digital signal. This digital signal is sent through a serial output to a computer. It can be studied from the computer's Visual Display Unit as a graphical output for further processing or for conclusions to be drawn from it [27, 28, 29]. We use programming to process the signal so that the command the user wants to send to the car can be determined. Various gestures create unique EMG signals. Unique signals are responsible for the forward, reverse, turning left, and turning right movements of the Moorebot Scout (Fig. 6).

Figure 6: The Moorebot Scout [30]

The BIOPAC MP36 data acquisition unit is well suited for our study because it has some unique features, including a 24-bit analogue-to-digital converter, a low voltage stimulator, the capability to accept inputs from multiple muscles and limbs with digital input & output capabilities, increased triggering options, ±2 Volts input range, the capacity to assess electrode impedance with a range of 1,000 K Ohm, and reduced noise on input amplifiers [31].

Figure 7: The BIOPAC MP36 data acquisition unit [30]

The data obtained from the BIOPAC MP36 data acquisition unit can be viewed using the BIOPAC student lab software. A screenshot of the user interface is shown in Figure 7. The electromyogram waveforms are shown in Figure 8. Figure 7 demonstrates four clench intensities (progressively lower to higher as we go from left to right). The signal underneath it is the root mean square signal that resulted after denoising, filtration, rectification, and smoothing procedures. Each wave was classified using a CNN into a separate gesture (Figure 9).

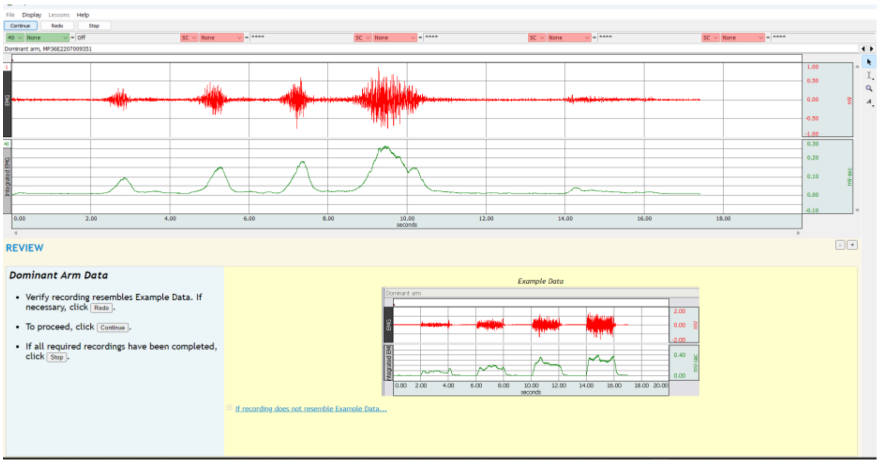

Figure 8: A screenshot of the user interface of the BIOPAC student lab software

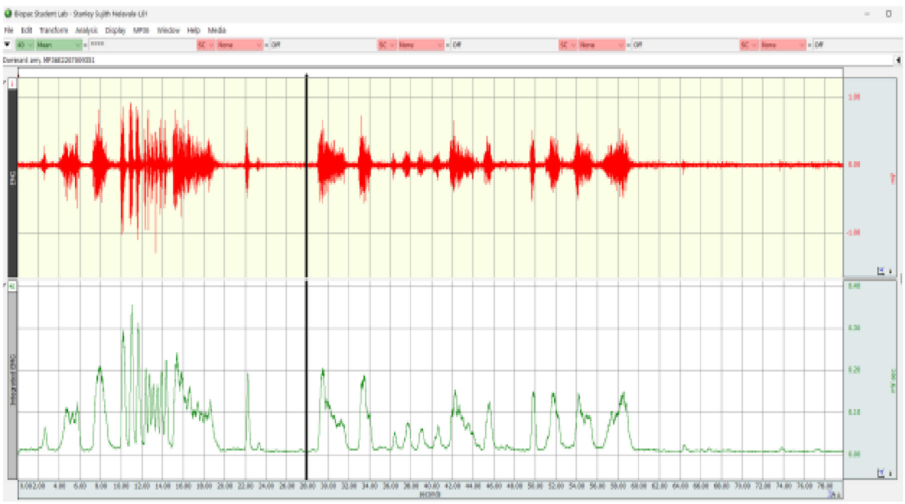

Figure 9: Electromyogram waveforms captured by us

The waveforms were extracted, analyzed, and classified in real-time using peaks [32], a Python package for interacting with BIOPAC's data acquisition system and executing real-time analysis of the generated waveforms. The BIOPAC File Format Application Programming Interface (ACKAPI) and a dynamic link library called acqfile.dll [33] were also installed and used to scrutinize the data in real time. Once classified, the signals were mapped to various movements of the Moorebot Scout: forward (accelerate), reverse (brake), turning left, and turning right, according to Table 1.

Table 1: Mapping the signals to movements of the Moorebot Scout

Move forward (accelerate)	Tightly opened palm
Move backwards (decelerate)	Very tightly clenched fist
Turn Right	Lightly clenched fist
Turn left	Sign of the horns

We attempted to integrate the Python program that classified the EMG waveforms into the Scout's software. We aimed to program the Scout and link the model to the Scout's user interface. We had to work with Scout's SDK for this (Figure 10).

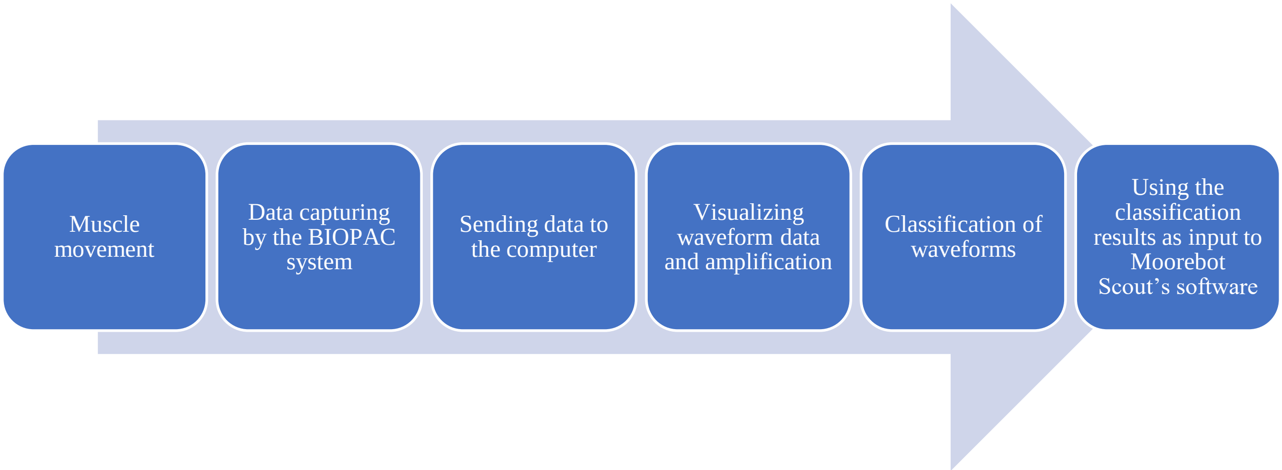

Figure 10: A block diagram of our system

5. Discussion

As robotic systems transcend the controlled confines of laboratories to enter the dynamic realm of the real world, the necessity arises for their augmentation with heightened robustness and autonomous capabilities. To confront the myriad environmental variances and increasingly intricate tasks, conventional approaches have leaned heavily on the augmentation of sensors and computational resources to inundate control systems with voluminous data. A parallel pursuit involves meticulously delineating operational contexts, the environment where the experiment is performed (in-situ, ex-situ, laboratory settings, etc.), and other task specifics.

Nature's simplicity reveals a paradox — most biological organisms exhibit complicated behaviours as they thrive efficiently while utilizing limited resources. Our proof of concept has explored a paradigm rooted in natural inspiration, aiming to construct a robotic framework and control system fostering emergent intelligence and resilience. This undertaking seeks to replicate nature's remarkable efficiency, aiming to birth robotic systems imbued with adaptive prowess and sophistication while judiciously managing resources like computational time and power requirements.

Mobile robots exhibit considerable potential in aiding humans in various scenarios. These scenarios range from aiding critical search and rescue operations amid disaster sites to fulfilling pivotal roles within industrial applications. Furthermore, their utility extends to the domain of security monitoring, where they serve as vigilant sentinels, bolstering surveillance efforts. Additionally, these versatile robots prove instrumental in executing tasks remotely within natural environments. Their adaptability and functionality empower them to navigate and operate effectively in diverse conditions, exemplifying their versatility and indispensable role in enhancing human capabilities across multiple domains.

We have shown how EMG signals can guide an external entity, the Moorebot Scout. The Moorebot Scout is controlled remotely using the Moorebot Scout App, which was virtually integrated with the BIOPAC MP36 software in real time. The Moorebot Scout robot has various technical specifications, making it a versatile and educational tool. Here are the details of its technical specifications and programming capabilities: Its programming capabilities display ease and advancement. It is compatible with the Scratch programming language, making it suitable for entry-level programmers and STEM education. It can also run C/C++ programs for advanced developers. The open API allows advanced users to design and create extension tools, expanding the robot's capabilities.

The peak code we utilized for this purpose possessed considerable intricacy. It revealed certain bugs which had to be conscientiously removed. The dll file was expensive and had to be obtained from a third-party source.

Our project attempts to overcome the requirements of tedious hardware connectivity by relying fundamentally on software integration. However, this advantage translated into a definitive handicap. One of our project's drawbacks was the delay in translating the signal into the intended action. While the accuracy of the InceptionV3 model was high, it could not be caused to be prompt enough to produce an output and generate the desired movement in the Scout. Potential delays were as high as 4200 microseconds between the generation of the signal and the output.

6. Results

Our implementation involved leveraging the Moorebot Scout using EMG (Electromyography) signals collected via the BIOPAC MP36 Data Acquisition system. This innovative approach highlights many advantages, particularly within the disabled community. By harnessing EMG signals, fundamental tasks such as activating and deactivating electric switches, operating household appliances like dishwashers, and controlling water heaters can be seamlessly executed if disabled people utilize this technology. This technology simplifies daily activities for individuals with disabilities, empowering them to manage essential tasks independently within their environment.

The potential of our proof of concept extends beyond basic functionalities. It showcases promise in facilitating communication for individuals with hearing or speech impairments. The system demonstrates potential in translating sign language gestures into textual output through its capacity to interpret EMG signals. This breakthrough has immense implications for enabling smoother and more inclusive communication between individuals proficient in sign language and those unfamiliar with it.

While our system has exhibited limited success, further advancements can optimize its performance. Integrating additional gestures and mapping them to diverse outputs is a potential enhancement avenue. By expanding the repertoire of recognized gestures and associating them with various tasks or commands, the system can evolve to accommodate a broader spectrum of user needs and preferences.

Our current system not only showcases the transformative potential of EMG-driven technology in simplifying daily tasks for individuals with disabilities but also hints at broader horizons, such as facilitating cross-communication between individuals with different modes of expression. Continual advancements and refinements promise to make this technology even more accessible, versatile, and impactful for diverse user groups in the future.

Expanding the system's capabilities involves augmenting its performance by integrating an expanded array of gestures, which can be meticulously mapped to diverse and multifunctional outputs. The system's versatility and usability can be significantly amplified by broadening the spectrum of recognized gestures and intricately associating them with various output possibilities. This enhancement strategy allows for a more comprehensive repertoire of user-initiated actions and paves the way for a more intuitive and personalized user experience.

Moreover, the strategic incorporation of additional gestures aligns with the overarching goal of refining the system's adaptability, making it more adept at understanding and responding to an extensive range of user inputs and commands. Through this evolution, the system is poised to cater more effectively to its users' diverse needs and preferences, fostering greater efficiency, accessibility, and utility in its operations (Figure 11).

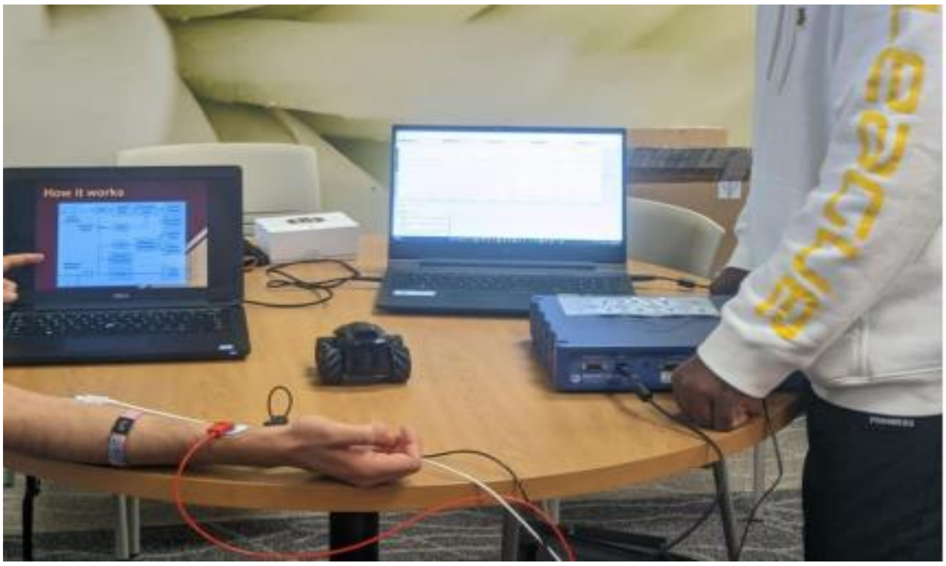

Figure 11: Demonstration of our project

7. Conclusions

Our project, MuscleDrive, described in this paper, seeks to provide new insights into the arena of Human-Computer Interface and EMG-operated vehicles. The EMG signals given are recognized using neural networks on a local server. However, there is a lag in processing; therefore, its processing cannot exactly be called real-time due to the delay. The project integrates the Electromyography (EMG) technology and the Moorebot Scout with partial success. It offers potential applications in various settings and demonstrates the system's adaptability. The innovative project shows the promise of versatility and multifaceted applications across diverse settings. It exemplifies efficacy. The system can be tailored to meet the requirements of different industries, facilitating adjustments and integration of gesture-controlled switching applications. Therefore, it highlights its far-reaching potential across sectors, underscoring a transformative impact in diverse operational environments. The project raised little safety and environmental concerns. Since most of the project is software-based, safety and environmental concerns have been minimized. The EMG utilized for generating physiological output for the project was surface EMG, which prevented any possibility of the spread of blood-transmitted disease. There was little possibility of getting an electric shock from the EMG device because of safeguards like earthing. Additionally, BIOPAC is a reliable manufacturer with a proven track record of safety in education and research initiatives. Some of the potential applications of the system have already been discussed. The primary use case for which we want to develop MuscleDrive into a system that can be used to drive an actual car to allow people with paraplegia, hemiplegia, quadriplegia, amputated limbs, or other problems to be able to drive a vehicle without external assistance essentially.

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Ethics and Consent Statement: The consent was obtained from the colleges during data collection, and ethical approval and participant consent were received.

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