2023 年臺灣國際科學展覽會
優勝作品專輯

作品編號	**100039**
參展科別	工程學
作品名稱	**Conscious Brain Mind-Controlled Cybonthitic Cyborg Bionic-Leg - V2**
得獎獎項	

國　　家 **Egypt**

就讀學校 **El-Sadat STEM School**

指導教師 **Doaa Gamal Elhosieny Tahoun**

作者姓名 **Moaz Mostafa Allam**

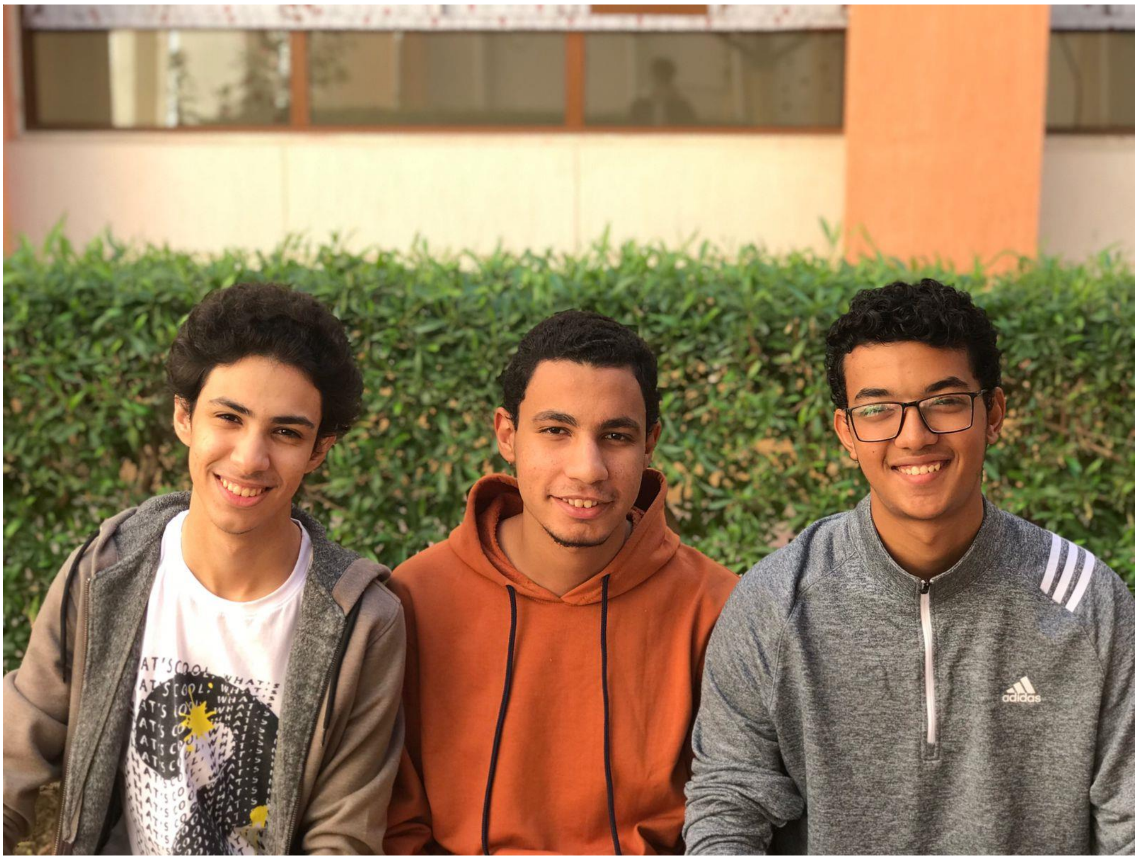
Ahmed Ayman Mohammed Abd El-Monsef

Mohammed Sabry Abd El-Samee Lasheen

關鍵詞 **sEMG、Prosthetic limb、Lower limb Amputation**

作者照片


NASA


adidas

Abstract*—Lower limb amputations affect about 28.9 million people worldwide, influencing normal human functions, we are developing a conscious brain mind-controlled Cybonthitic cyborg bionic-leg to provide a professional solution for this problem, which is classified as restricted knee movement, short-term solution, limited pressure bearing, unspecific analog reading of EMG; Because the output voltage measured in nano-volts, resulting in unspecific knee movement. The functionality of these modern gadgets is still limited due to a lack of neuromuscular control (i.e. For movement creation, control relies on human efferent neural signals to peripheral muscles). Electromyographic (EMG) or myoelectric signals are neuromuscular control signals that can be recorded from muscles for our engineering goals. We worked on a sophisticated prosthetic knee design with a 100-degree angle of motion. We also used a specific type of coiled spring to absorb abrupt or unexpected motion force. In addition, we amplified the EMG output from (Nano-Voltage) to (Milli-Voltage) using customized instrumentation amplifiers (operational amplifiers). We used a full-wave rectifier to convert AC to DC, as a consequence of these procedures, sine-wave output voltage measures in millivolts, and the spring constant indicates the most force for every 1cm. Von mises Stress analysis shows bearing as 3000N is the maximum load for the design. Detecting the edge of a stairwell using the first derivative. The benefit of a system that controls the prosthetic limb is activated by the patient's own EMG impulses, rather than sensors linked to the body.

I. Introduction

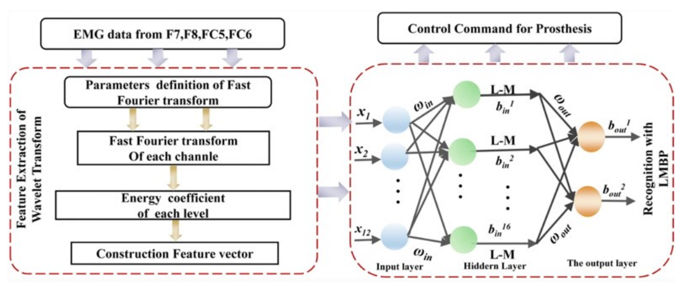
A prosthesis is a term that refers to an artificial device that replaces a physical component or organ. A prosthetic leg replaces a lower limb that has been amputated for many reasons. The National Limb Loss Information Center supplied the amputation data in that there are roughly 1.7 million people living with limb loss in the United States [5]. A Myoelectric A prosthetic leg, as the name indicates, is a prosthetic leg which employs myoelectric (EMG) impulses for control. This is feasible owing to the fact that the neuro-muscular system of amputees remains intact even after amputation. The remaining signals are made use of, and they are adequate enough to control the movement of the leg after proper processing [6]. Actuators such as motors are employed to replace the function that muscles perform by delivering force for movement of the leg. Myoelectric prosthetic legs stand apart from externally powered legs, which rely on external power for controlling the limb from pulses that are sent from your brain.

II. Methods

A. sEMG Signal Processing

Electromyography signals are used to determine the electrical activity of muscle fibres during contraction and rest. Two approaches are used to capture these myoelectric signals: invasive and noninvasive. Invasive methods use needle electrodes to record the sEMG signal. However, noninvasive is often preferable, since it is positioned right above the skin surface without requiring the electrode to be inserted into the patient's body. Numerous issues such as motion artefacts, electrode misplacement, and noise interpolation all have an effect on the EMG signal. To extract additional information, signal processing techniques including as filtering, rectification, baseline drifting, and threshold levelling are used to EMG signals. The block diagram of the EMG signal processing is depicted in (**figure 1**).

Fig. 1. Neural network for signal processing. Adapted from Medical and Biological Engineering and Computing

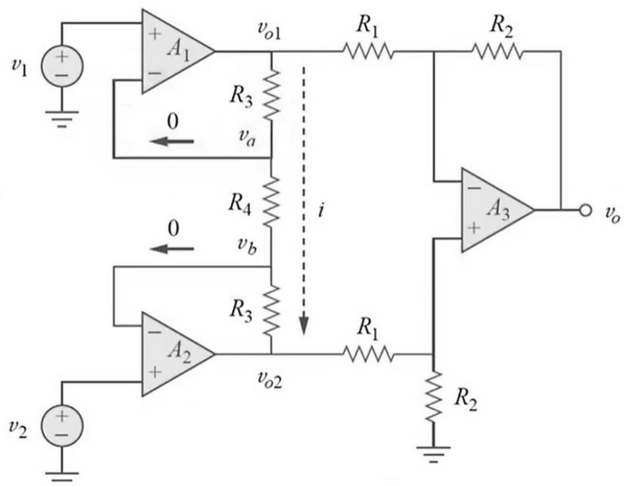


As shown in (fig 1) The fast Fourier transform (FFT) steadily transforms a time-domain signal into different frequency scales. Hence, the FFT was selected to extract EMG features in this study. The statistical parameter of FFT energy coefficients can be obtained using the following equation:

$$\sum_{i=1}^{n} y_i^2 (j = 1, 2, 3, 4) \tag{1}$$

Three pre-gelled surface electrodes are used to capture EMG data for limb rotational movement. Two electrodes are inserted into the limb's acromial and clavicular portions of the central deltoid muscle (anterior fibers). For efficient grounding, the other portion is equipped with a ground electrode. Surface electrodes are used to detect EMG signals. However, the selected signal has an amplitude of microvolts. Thus, a preamplifier is required to convert the microvoltage EMG signal (μV) to millivoltage (mV). The EMG signal is delivered into the preamplifier directly from the electrode. Using Instrumentation Amplifier (IA) as shown in (fig 2) cause having a high CMRR, a high input impedance, fixed gain for amplification, and high-low pass filtering.

Fig. 2. Instrumentation amplifier and its gain

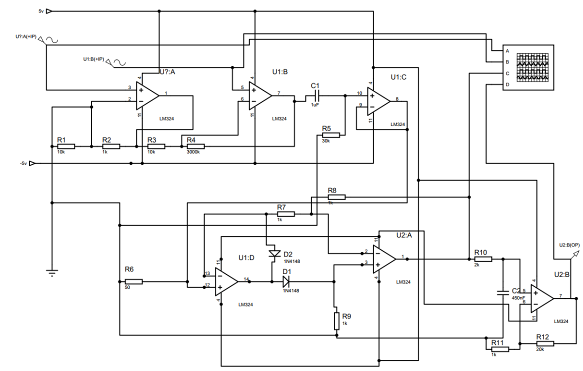


As An instrumentation amplifier (IA) is used to provide a large amount of gain for very low-level signals, often in the presence of high noise levels. The major properties of IAs are high gain, large common-mode rejection ratio (CMRR), and very high input impedance
Features : Instrumentation amplifiers are precision, integrated operational amplifiers that have differential input and single-ended or differential output. Some of their key features include very high common mode rejection ratio (CMRR), high open loop gain, low DC offset, low drift, low input impedance, and low noise.

B. High and Low pass filtration

In order to eliminate the high frequency signal, the output of the preamplifier is fed into low pass filter. To design an effective filter, comparison is done with various filter topologies. as shown in (fig 3) that HPF and LPF are critical in filtering pulses that have been amplified. The EMG signals that have been saved are processed. To eliminate motion artefacts and external noise from the collected EMG data, a high pass filter with a cutoff frequency of 20 Hz is used. For stop band attenuation, a fourth order Butterworth high pass filter has been used. When examining muscular contraction, it is recommended to select dominant EMG signals with a frequency range of 20 Hz - 500 Hz. The EMG signals are corrupted by noise.

Fig. 3. Schematic diagram for sEMG PCB



C. RECTIFICATION AND AMPLIFICATION

A corrected signal is required. The goal of rectification is to eliminate the signal's negative components. By eliminating the negative components, the negative amplitude is converted to a positive value by squaring the total signal. As predicted, this step also squares the amplitude value. Additionally, if the amplitude is less than one, squaring would shift the amplitude away from one toward zero, lowering the value. Amplification is used to increase the signal's amplitude to a suitable level. The signal is multiplied by a constant value, which increases the amplitude of the whole signal by that amount. The output of this step is a positive signal (devoid of negative components) with an amplitude within the specified range.

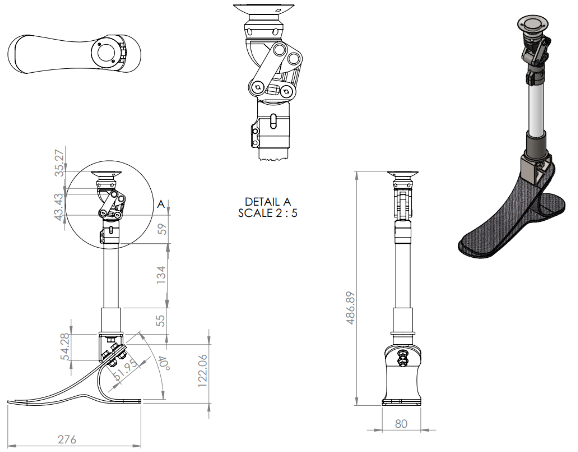
D. Smoothening

After the first few processing stages, the signal in hand still resembles an EMG signal in terms of contraction and relaxation phases, with the most noticeable difference being the conversion of negative components to positive ones after rectification. As previously stated, the contraction phase of the signal is the most interesting; thus, it must be separated from the remainder of the signal. This is accomplished by sending the signal through a low-pass filter that detects just the signal's envelope. Smoothing produces a signal with blunt peaks precisely during contraction stages.

E. Prosthetic Leg Model

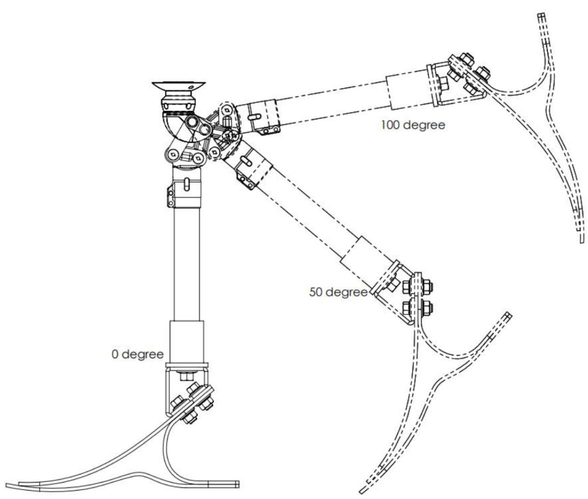
Making a prosthetic limb with a high bearing capacity, flexibility, comfort, and shock absorption for long-term usage requires considerable effort. When fabricating a prosthetic limb, it should be lightweight for ease of control and have a good load bearing capability. The prosthetic limb is constructed from lightweight but robust materials. The limb may or may not have functioning knee and ankle joints, depending on the site of the amputation. The socket is a very accurate cast of your residual limb that fits snugly over it. It assists in the prosthetic leg's attachment to your body. Suspension systems are used to secure the prosthesis, whether by sleeve suction, vacuum suspension/suction, or distal locking by pin or lanyard. As shown in (fig 4), numbers of models that are

Fig. 4. 3D design of prosthetic limb



created for achieving engineering goals such as high bearing capacity, light, and long-term use.
Following the selection of your prosthetic leg's components, you will need rehabilitation to strengthen your legs, arms, and cardiovascular system as you learn to walk with your new limb. You'll work closely with rehabilitation experts, physical therapists, and occupational therapists to develop a rehabilitation plan that is customised to your unique mobility requirements. Maintaining a healthy leg is a critical component of this routine.

Fig. 5. Angel of rotation



Real-life ration modeling for the prosthetic leg with 100 angel of movement as shown in (fig 5).

F. Machine Learning for Amputees

1) Detection Stairs: Using canny detection algorithm to detect edge as shown in (fig 6), and it analyzed data:
Noise Reduction:
Edge detection is sensitive to image noise, the first step is to eliminate the noise with a 5x5 or 3x3 Gaussian filter.

Finding the Image's Intensity Gradient:
The smoothed picture is then filtered in both the horizontal and vertical directions with a Sobel kernel to obtain the first derivative in both the horizontal (Gy) and vertical (Gx) directions.

$$Edge_{Gradient}(G) = \sqrt{G_x^2 + G_y^2} \tag{2}$$

We can find the edge gradient and direction for each pixel using equation(2).

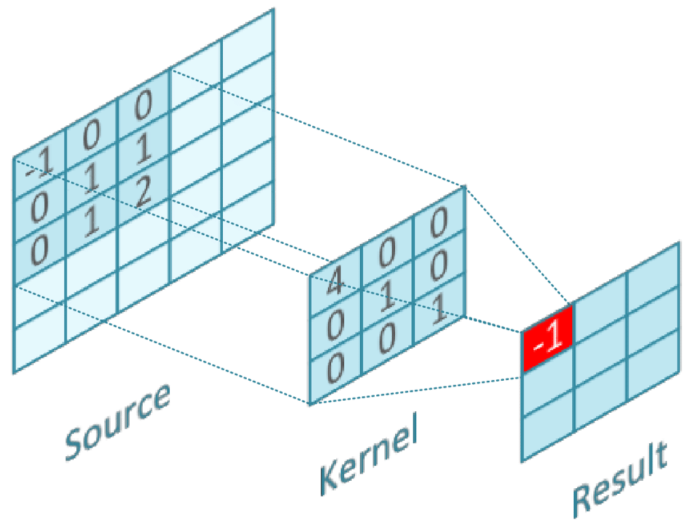


Fig. 6. A convolution of a 5x5 image with a 3x3 kernel.

2) Pattern recognition Algorithm: To estimate the intended joint trajectory, myoelectric signals and a pattern recognition algorithm may be used to forecast the user's locomotor mode. The intended locomotor activity may be anticipated by recognising patterns in the EMG data (i.e., since various locomotor activities can be assessed using distinct joint trajectories). Mechanical signals, in addition to EMG signals, may be analysed and utilised for pattern recognition. To discover patterns in myoelectric data, pattern recognition methods such as linear discriminant analysis and dynamic Bayesian networks have been applied. However, these algorithms may introduce significant delays, particularly when switching between locomotor activities. Successful intent classifiers have been created employing the forces at the human-socket connection, foot-ground contacts, myoelectric signals, and contralateral limb kinematics. It has been shown that including EMG signals and time history data into the control system considerably reduces classification mistakes during human prosthesis locomotion. Researchers have shown that unilateral transtibial amputees can forecast locomotor activity using myoelectric signals from the undamaged biological knee joint. By collecting signals and identifying the greatest and minimum values for data visualisation, we can foresee the appearance and movement of muscles using the candlestick technique for pattern recognition. As the largest value is considered resistance, while the least value is considered support. Max and Min values are gathered and used as reference points for prediction, as they are included into the formula for prediction:

$$\tilde{x_i} = \frac{(x_i - max(X)) + (x_i - min(X))}{max(X) - min(X)} \tag{3}$$

As data converted from 2d into 1D. Then, The segmented 1D data of the original time series are defined in this equation(3).

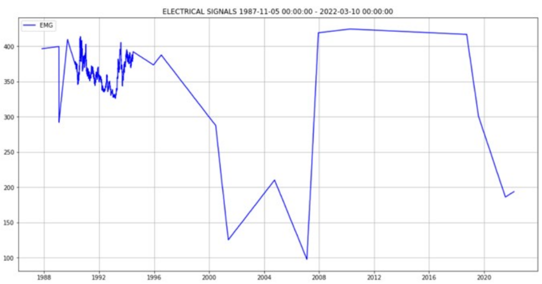


Fig. 7. Outputs of pattern recognition algorithm

As shown in (fig 7), By analyzing data, we can create a candlestick algorithm that predicts and recognizes any pattern. This is for the most exact movements of the bionic limb, since it is an excellent technique to forecast your movement and electrical pulse patterns.

III. Diagnostic Dystonia Using sEMG

Runner's dystonia (RD) is a task-specific focal dystonia of the lower limbs that occurs when running to diagnostic of dystonia. In this retrospective case series, we present surface electromyography (EMG) and joint kinematic data from thirteen patients who underwent instrumented gait analysis (IGA) at the Functional and Biomechanics Laboratory at the National Institutes of Health[1]. Four cases of RD are described in greater detail to demonstrate the potential utility of EMG with kinematic studies to identify dystonia muscle groups in RD. Lateral heel whip, a proposed novel presentation of lower-limb dystonia, is also described.

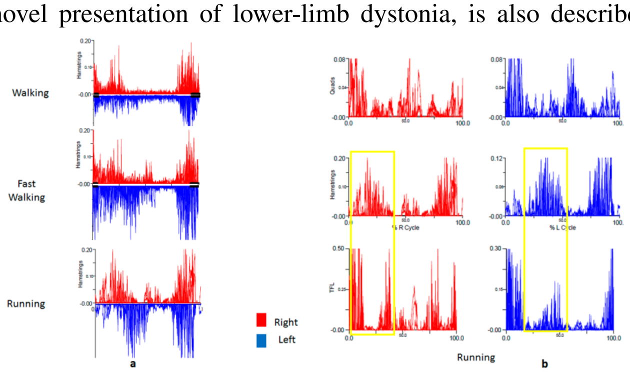


Fig. 8. sEMG of a patient with runner's dystonia presenting as task-specific. Adapted from ncbi.nlm.nih.gov

Surface EMG is showing continuous activity in the left hamstrings (b) and early activity in the left tibialis anterior during running (a). Showing how left leg delayed in activation of motor neuron with respect to other leg as shown in (fig 8).

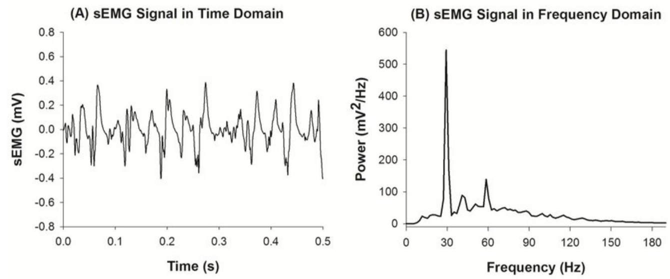


Fig. 9. Surface electromyography (sEMG) signal of the Vastus Lateralis during wholebody vibration at 30 Hz illustrated in (A) the time domain and (B) the frequency f_0 domain. In the frequency domain, excessive spikes are visible at the vibration frequency and its multiple harmonics.

(A) in the time domain and in (B) in the frequency domain. The signal was recorded from the vastus lateralis (VL) muscle during Whole body vibration (WBV) at 30 Hz. While the sEMG signal in the time domain does not highlight any specific characteristics to WBV. The sEMG signal in the frequency domain clearly shows excessive spikes at the vibration frequency and at a few multiple harmonics and that means how dystonia is diagnostic obviously. At the same time, and also for preliminary purposes, the electrophysiological signal was recorded from the patella during WBV. Such a signal obtained during WBV at 30 Hz is shown in Figure 9. In the time domain, the patella signal resembles a sinusoidal wave at 30 Hz. In frequency domain, excessive spikes are observed at the vibration frequency and to a lower extent at its multiple harmonics. No myoelectrical activity is shown for all the other frequencies.

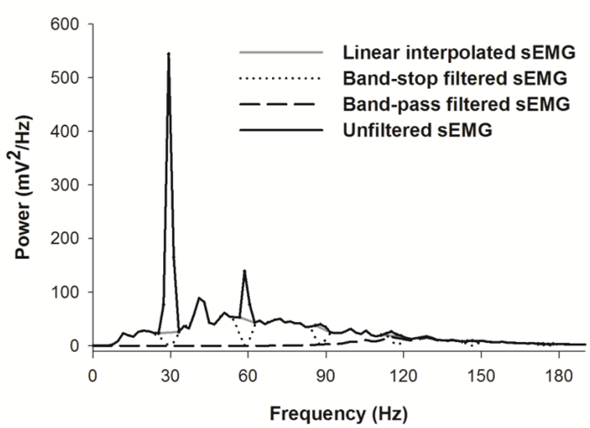


Fig. 10. sEMG signal processing methods in dystonia diagnostic. Adapted from Universite De Nice Sophia Antipolis

A surface electromyography (sEMG) spectrum of the Vastus Lateralis during whole-body vibration at 30 Hz. sEMG signals were processed using the no-filter method (black solid line), linear interpolation (grey solid line), band-stop filter (grey dotted line) and band-pass filter (black dashed line). As shown in Figure 10, The crucial role of filter especially High Pass filtration (HPF) and Low Pass filtration (LPF).

IV. Muscle Re-innervation Patterns

Strong EMG signals were elicited by the re-innervated hamstring muscles, notably during contractions related to ankle motions. When the patient flexed his knees, he noticed a lot of co-activation of re-innervated muscles (Fig.11).

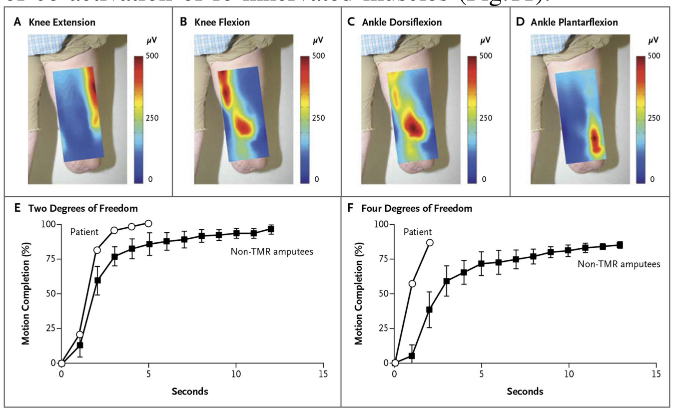


Fig. 11. Evaluation of Muscle Re-innervation Patterns, electrical pulses were conveyed in both amputees and normal humans. Adapted from The new England Journal of medicine.

Each attempted move resulted in different EMG signal patterns, implying that precise pattern recognition control was possible. With a virtual system configured to regulate ankle plantarflexion and dorsiflexion, as well as knee flexion and extension, the classification accuracy of the patient's attempted movements was 96.0 percent, and 92.0 percent with a system built to control tibial rotations and femoral rotation. In non-TMR amputees, classification accuracies for these attempted movements were 91.0 ± 4.7% and 86.8 ± 3.0%, Correspondingly. This amounts to a 5.0 percent and 5.2 percentage point boost in complete precision, correspondingly. TMR enhances real-time pattern-recognition control by 44 percent and 39 percent, respectively; these data imply that TMR improves real-time pattern-recognition control. Virtual movements were likewise completed more faster by the TMR amputees than by the non-TMR amputees. EMG data from the residual limb and mechanical-sensor data produced a unique stride pattern for each ambulation mode. The inclusion of EMG information increased the accuracy of the control system. With the use of mechanical-sensor data only.

V. Results

For finding the factors that may affect results. It is tested in various conditions. Test on 3 channels of EMG that collect electrical pulses. This shows how movement and shaking of your body affect and make noise in data when it collects. As shown in this graph when there is no cable movement, there is no noise in data. But when slow or fast cable movements, this makes spike, and noise in data. So, by using p300 algorithm, and low-pass filtration, it removes noise and spike to return to original value of it as shown in (Fig. 12).

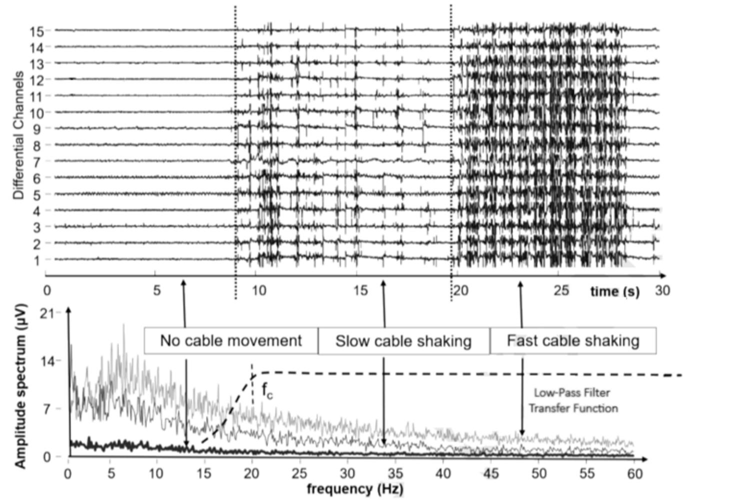


Fig. 12. Low Pass Filtration for reject and filter noise in background.

As shown in (Fig. 13), How electrical impulses from an EMGs sensor are gathered, and how to display the data. It became negative and positive sides as it accumulated without any invert in waves. We employ Ins Amp and Op Amp to invert and integrate these data to address the problem. Then, to convert it from ac to dc, we utilize full wave rectifiers, which will make it easier to store the data. Low pass and high pass filters are crucial in cancelling any noise when data collected.

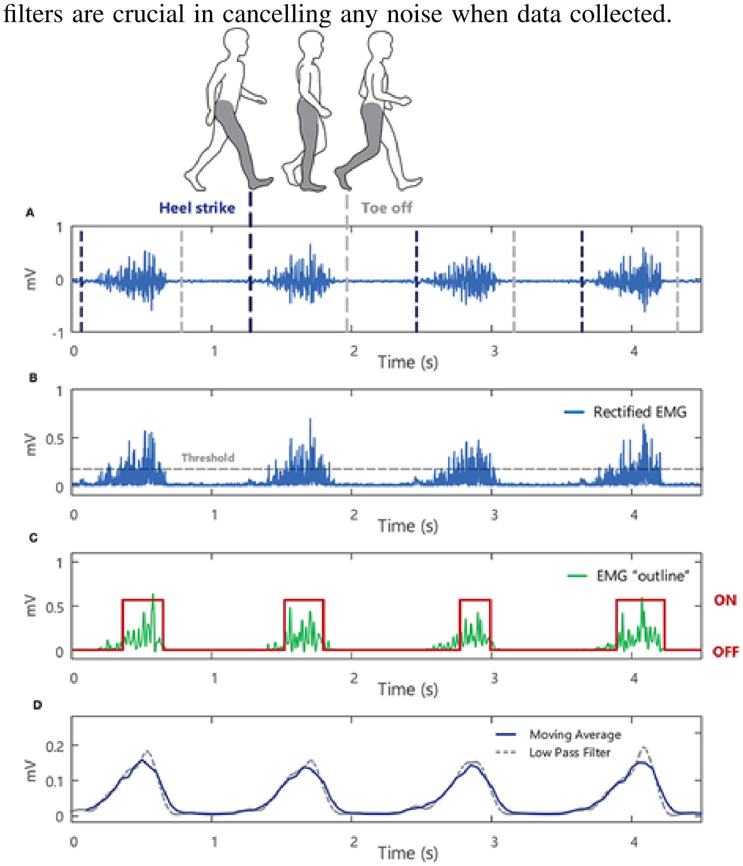


Fig. 13. Mechanism of electrical pulses From sEMG to captured it

A. Piezoelectric and Voltage generator

Piezoelectric Effect is the ability of certain materials to generate an electric charge in response to applied mechanical stress. When piezoelectric material is placed under mechanical stress, a shifting of the positive and negative charge centers in the material takes place, which then results in an external electrical field. When reversed, an outer electrical field either stretches or compresses the piezoelectric material. Using piezoelectric devices to recharge batteries. It is necessary to test numerous times to see if it is suitable to be main voltage generator.

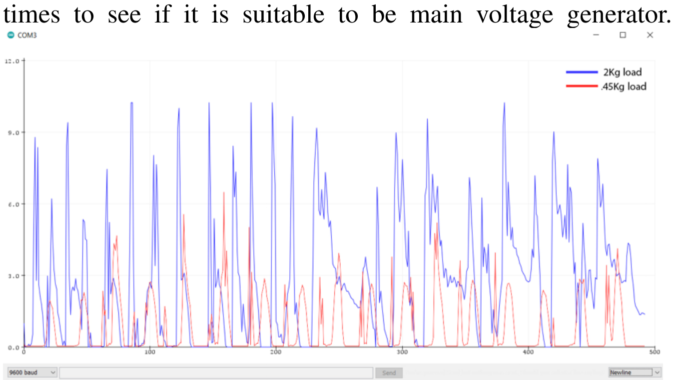


Fig. 14. Piezoelectric Results that differed by increase load

As demonstrated in the graph, as the load increases, so does the voltage. The output was sufficient for being main voltage generator.

B. Stress Analysis of Presthestic limbs

For Design Prosthetic limb needs to have a high bearing capacity, flexibility, comfort, shock absorption, long-term use. For design, a prosthetic limb needs to have a high bearing capacity, flexibility, comfort, shock absorption, and long-term use.

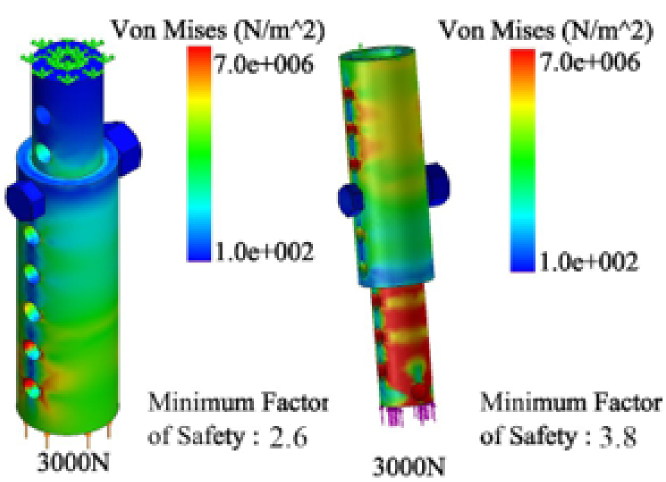


Fig. 15. Von-Mises Stress analysis diagram, simulate the maximum load which the leg can effort. As shown in figure, the Max load the leg can bear approximately 3000 newtons.

VI. CONCLUSION

In this study, EMG signal is successfully extracted from the subject and the acquired EMG signal has two parts: relaxation phase and contraction phase. The contraction phase is what we are interested in for proceeding with the work. In order to control the motor rotation using the EMG signal, the contraction phase is made use of, for which it has to be processed suitably to result in a pulse output whenever the muscle is contracted. The steps involved in processing are those which convert the EMG signal into pulsed output for each contraction. The final output is a pulsed signal where each pulse corresponds to muscle contraction. When considering prosthetics limb, more degree of freedom is required. So our future work extends to signal classification such as K-means algorithm and support vector machine.

REFERENCES

[1] Ahmad, O. F., Ghosh, P., Stanley, C., Karp, B., Hallett, M., Lungu, C., and Alter, K. (2018). Electromyographic and joint kinematic patterns in runner's dystonia. Toxins, 10(4), 166.

[2] Bates, T. J., Fergason, J. R., and Pierrie, S. N. (2020). Technological advances in prosthesis design and rehabilitation following upper extremity limb loss. Current Reviews in Musculoskeletal Medicine, 13(4), 485-493.

[3] Beyrouthy, T., Al Kork, S., Korbane, J. A., and Abouelela, M. (2017). EEG mind controlled smart prosthetic arm-acomprehensive study. Advances in Science, Technology and Engineering Systems Journal, 2 (3): 891-899.

[4] Farnsworth, B. D., Triolo, R. J., and Young, D. J. (2008). Wireless implantable EMG sensing microsystem (pp. 1245-1248).IEEE.

[5] Jun-Uk Chu, Member, IEEE, Inhyuk Moon," A Supervised Feature-Projection-Based Real-Time EMG Pattern Recognition for Multifunction Myoelectric Hand Control 44, IEEE/ASME Transactions on Mechatronics, vol. 12, no. 3, June 2007, p. 282-290

[6] Kathryn Ziegler-Graham, PhD, et al. "Estimating the Prevalence of Limb Loss in the United States - 2005 to 2050," Archives of Physical Medicine and Rehabilitation 89 (2008), p. 422-429.

[7] Kim, K. T., Park, S., Lim, T. H., and Lee, S. J. (2021). Upper-Limb Electromyogram Classification of Reaching-to-Grasping Tasks Based on Convolutional Neural Networks for Control of a Prosthetic Hand. Frontiers in Neuroscience, 15.

[8] Mark L. Edwards, Olson, D. A. and DeRuyter, F., (2002). Chapter 18 - Lower Limb Prosthetics. In Clinician's guide to assistive technology. Mosby.

[9] McDonald, C. L., Westcott-McCoy, S., Weaver, M. R., Haagsma, J., and Kartin, D. (2020). undefined. Prosthetics and Orthotics International, 45(2), 105-114. https://doi.org/10.1177/0309364620972258

【評語】100039

1. The work presents the design of a prosthetic limb and the use of EMG data for the motion control. A conscious brain mind-controlled Cybonthitic cyborg bionic-leg is investigated to provide a professional solution for this problem，which is classified as restricted knee movement，short-term solution，limited pressure bearing，unspecific analog reading of EMG; Because the output voltage measured in nano-volts，resulting in unspecific knee movement.

2. The functionality of these modern gadgets is still limited due to a lack of neuromuscular control (i.e. For movement creation，control relies on human efferent neural signals to peripheral muscles). Electromyographic (EMG) or myoelectric signals are neuromuscular control signals that can be recorded from muscles for our engineering goals.

   An overall diagram of the so-called brain control to bionic leg is recommended to provide a sketch of the system and highlight the new contribution (if any) of the proposed work. A quantitative analysis about the positioning accuracy and response time is also deemed useful to verify the design.