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Utilizing EEG Signal Data and Motion to Aid in Prosthetic Hand Motion

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ABSTRACT

Current prosthetic arm technologies are often difficult to use intuitively by amputees, require invasive surgical procedures, and can be extremely costly with prices ranging from $20,000 to $80,000. To address these challenges, the engineering goal of this project aims to design a smart, low-cost, mind-controlled transhumeral prosthesis by integrating the brain-interfacing capabilities of electroencephalography (EEG), the economical means of 3D printing technology, and gesture-detecting attributes of an accelerometer-gyroscope. Single-channel brain signals are transmitted through Bluetooth to be interpreted by a novel EEG decoding algorithm and head gestures from the inertial measurement unit actuate movement within the arm. Force sensitive resistors were employed to regulate force control in real-time to optimize grasp type. An LCD screen is integrated within the arm's design to display the type of touch it is exerting on an object. The arm itself was printed with an original design utilizing PLA plastic filament making it extremely durable and lightweight. After thoroughly testing the prosthesis, the novel EEG decoding system boasts an accuracy of 94.7% and a user cognition to machine delay of 1.64 + - 0.37 seconds. The inertial measurement unit system recognizes user gestures with a delay of .136 seconds. With a bill of materials approximately $375 USD and ability to be moved in 4 degrees of motion, this novel upper limb prosthesis serves as a promising alternative to existing units on the market. The algorithms developed within this project have a wide range of use within other brain control interface projects.

Introduction

Upper limb amputations are catastrophic for individuals, leaving intense functional and mechanical disabilities. These amputations severely reduce the quality of life for affected individuals and restrict daily activities. Estimated globally, 65 million people live with limb amputations, with 40% of cases resulting in upper limb amputations, and 1.5 million people undergoing amputations every year. The factors that cause limb amputations include but are not limited to: state specific examples of what causes limb amputations – accidents, diseases, etc. In the US alone, approximately 1.7 million people live with a form of limb loss, which translates to 1 out of every 200 people. Compared to lower limb loss, transhumeral extremity amputation makes up about 6% of the worldwide amputee population (3 million people) and 3% of the US amputee population (41,000), which often results in scientists to overlook this area of research for future development. Although prosthetic limbs have existed since the 16th century, and despite advancements in intellectual dexterity, durability, and flexibility, current technologies and solutions lack affordability. Currently, two thirds of the amputee population, and 80% of all arm amputees live in low resource settings such as rural areas of Cambodia and India with limited access to forms of support or rehabilitation. Low resource settings are prone to fatal accidents and injuries, increasing risk of amputations with limited healthcare. (Maduri, 2022)

Upper limb amputation procedures tend to be invasive and require precise, complex surgery. Medical procedures serve to reassign nerves in cohesion with the prosthetic, allowing the amputee to control the prosthetic with their minds, improving their quality of life and daily activities. The costs of these transhumeral prosthetics range from $10,000 to $30,000. The John Hopkins Applied Physics Laboratory has developed a mind controlling prosthetic arm, consisting of 26 joints and capable of lifting 45 pounds. This arm is controlled by brain signals, with six microelectrode arrays inside the brain in various areas. According to the John Hopkins researchers, their limb costs a couple thousands of dollars. Surgical implantation connects the arm to the torso, where connections are rewired through the nerves allowing the readings of raw electrical signals to later be converted into commands. However, this method is extremely invasive, welcoming the path for further complications such as heart disease, paralysis, and deadly infection. Surgical implantation also does not address the economical means of the patient, which rules out the possibility to serve low income areas. Another method of control consists of using non-invasive sensors to collect brain activity, which will ultimately be decoded into commands for the robotic arm. Recent procedures have made use of electroencephalography (EEG) and electromyogram (EMG). Users would be able to control the prosthetic arm with their mind or allow neighboring muscle data to direct the arm. These options have proven to be extremely cost effective, with EEG prices starting at just $100 USD. These EEG sensored arms provide high accuracy and the luxury of flexibility when feeling discomfort for the user. The profound connection between the brain and the prosthetic is performed via brain computer interfaces. Brain Computer Interfaces (BCI) is an emerging field, where an external source and the brain harness a direct communication pathway. Forms of electrical, magnetic, and other physical manifestations of brain activity are collected and translated into commands on an external device, through signal processing and classification of data patterns. The most common, non-invasive data collection method is through an EEG, electrodes are placed on the head, exposing the oscillatory activity within the frequency bands. These neural oscillations are used as indicators for certain neurological phenomena, including stages of sleep, memory, processing, and abnormal functions.

The project discussed in the paper aims to develop a smart, low-cost, anthropomorphic, prosthetic arm by integrating the brain computer interfacing applications of an EEG, precise movement of a gyroscope accelerometer, and the ultra-low cost advantages of a 3-D printer. (Maduri 2022)

Materials and Methods

Model Design

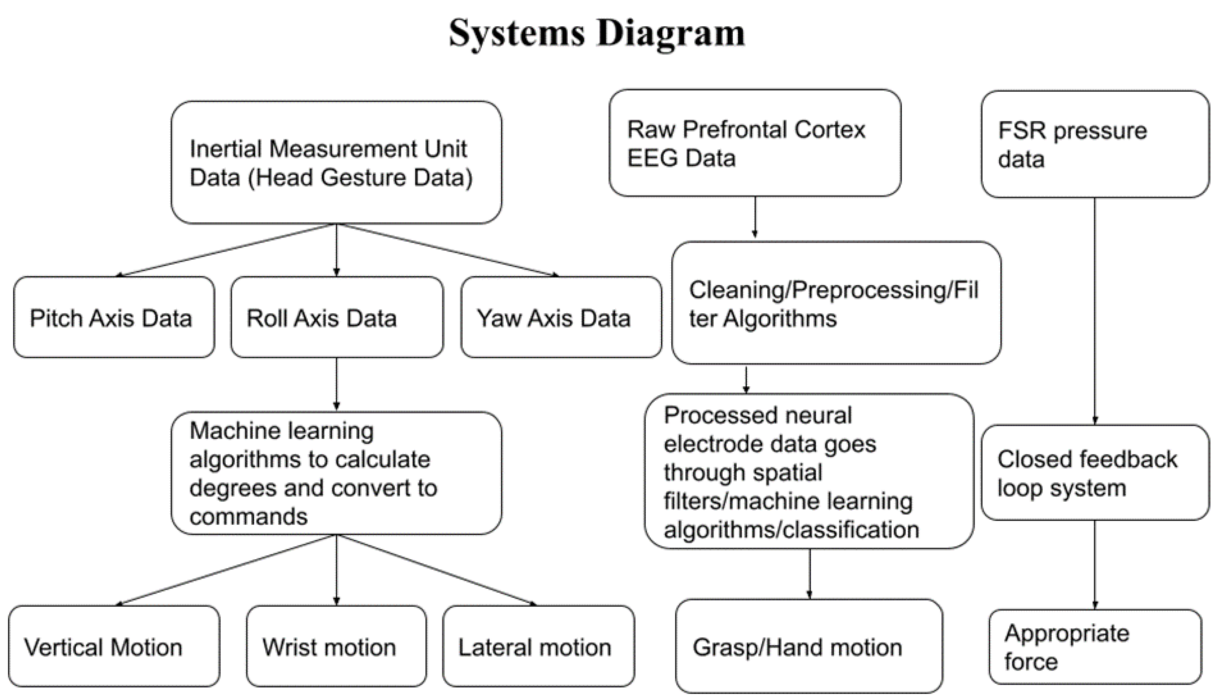

Figure1. An overview of the of the prosthetic software systems diagram

EEG data is collected from the MUSE EEG Headset, a wearable device designed to provide real time feedback on brain activity. Via Bluetooth, this data is sent to the Arduino Mega, and is filtered and read through machine learning algorithms. When the machine learning algorithms detect a beta wave in the binary data, the Arduino sends commands to servos, to actuate grasp movement in the hand. Vertical and horizontal movement is detected through the MPU3050 gyroscope and accelerometer. Data from the MPU6050 is decoded through code from the Arduino which is translated to X, Y, and Z movement through commanded sensors.

TinkerCad online modeling software was used to create the original 3D model of the prosthetic arm. This model consisted of 5 finger pieces (including a thumb), a palm, a wrist, and forearm. Each finger, except the thumb which has only 1 divot, has 3 divots to allow for flexion/extension of the hand piece. The wrist and forearm pieces are essentially empty boxes with covers to store both servo motors. The front, or head, of each piece has a hollowed out rectangle to allow for easy attachment to prior pieces of the entire model. Additionally, the forearm piece holds a single Arduino Uno which serves as the central processing unit (CPU). All pieces of the arm were sliced through Cura and printed on a Ender 3 V2 Neo 3D Printer.

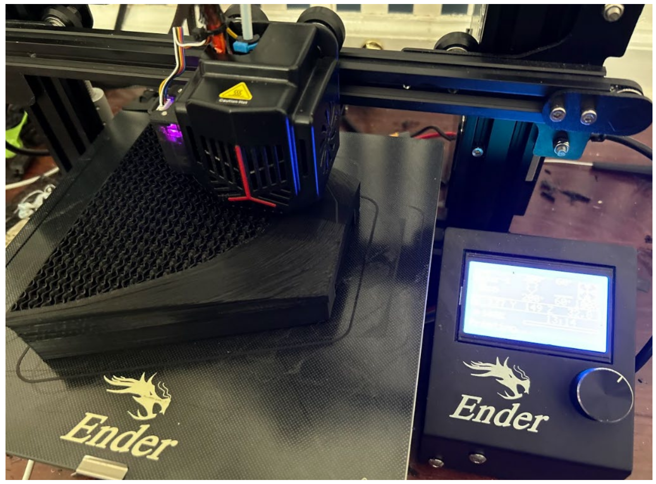

Figure 2. 3d printing of prosthetic arm

Preprocessing

The data was split into training (60%), validation (20%), and test sets (20%) once 30 CSV files from the MUSE Headset, an EEG headset that provides real-time feedback on the user's brain activity. The MUSE data is sent to a Bluetooth Module hand attached to the back of the MUSE headset, which is then sent to the Arduino Mega Microcontroller Unit. Outlier detection algorithms were used based on a mixture model, a model used to represent data in various subsets and groups. Outliers were determined if the datapoint was considered farther than the fitted distributions. With EEGs proving difficulties in single distributions, a mixed model was used, combining distributions for a more accurate representation. To determine the noisiness of the data, the Power Spectrum Density (PSD) was plotted. The PSD uses a Fast Fourier transform along a variation of signals to compute the frequency range. The PSD showed the noisiness of the data, with high peaks in the upper frequencies. The data was then epoched into segments of 3 seconds.

Spatial Filtering and Feature Extraction

Spatial filtering rises to importance due to the poor spatial resolution of the EEG, which is the result of the thousands of active neurons. Raw EEG signals are high dimensional, proving unsuitable for direct input and require dimensionality reduction. Another reason to prohibit the use of raw EEG data as a main feature vector is due to the additional amount of data needed as the dimension grows to generate a high accuracy (known as the curse of dimensionality). Thus, specific features of the EEG are extracted. Spatial filtering linearly combines signals from a multitude of electrodes, increasing the signal-to-noise ratio, a measure used to compare the desired signal to the amount of background noise, and ultimately makes it easier to identify the origin of the signal. For this project, a spatial-frequency filter extracted from the Common Spatial Pattern (CSP) algorithm was used. The general framework is to maximize the variance of one condition while minimizing the other, which is performed by breaking a multivariate signal into additive components. This filters the data, clearly illustrating the features with the most variance and those with the least. First, band-pass filters are applied to the raw EEG data to acquire beta wave frequency bands. The CSP algorithm is then applied to every filter result to extract the desirable spatial features. Feature selection algorithms are used to select the most prominent features among the spatial filters.

Classification

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Previous literature of BCI creations revolve around using motor imagery or eye blinking patterns as key classifiers for commands (Bhuyan, 2014). However, this project is one of the first to leverage data from attention bursts in beta waves. In many BCI's the most used classifiers are discriminant classifiers, specifically Linear Discriminant Analysis (LDA) classifiers. LDAs are generally used due to their simplicity, making them exceptional at generalizing new data. Another known classifier, a Support Vector Machine (SVM) was used due to its generalization abilities and resistance to the curse-of-dimensionality. The goal of a LDA is to find a projection vector that maximizes the separability of the feature vectors. Since this prosthesis was coded on an Arduino, original algorithms were developed. Inspired by the LDA algorithm, the algorithm projects the multidimensional vector into one dimension. The difference between the projections are maximized while interassociations are minimized. Two classes are assumed to distribute with different means but identical covariance matrices.

Support Vector Machines learn features by classifying them and constructing a linear hyperplane, which dissociate classes. Properties and ideas from the support vector machine were taken. The general benefit of our algorithm is designed for multi-class classification. It has the ability to be a linear classifier, but also perform non-linear classification systems by constructing hyperplanes in higher dimensional space. This allows data that cannot linearly separate to detach in original input space. A discrimination is then found in the hyperplane between the classes, and combined using a maximization rule. This is performed using a Gaussian kernel, which uses a kernel function to map and data and compute inner-product between two vectors. Once the spikes of concentration in the beta waves are classified, they are sent to the servos to control the grasps and hand motions of the prosthetic.

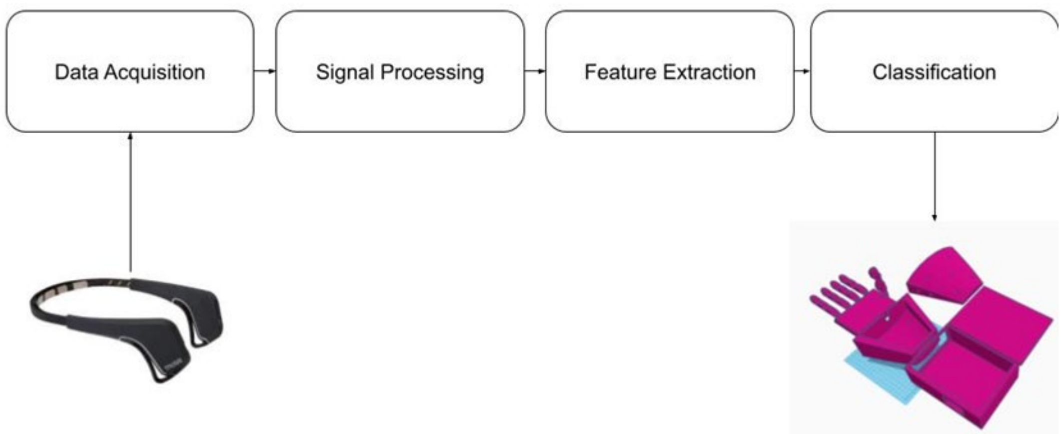

Figure 3. Machine Learning Hierarchy

Gyroscope/Accelerometer

The movement of the robotic arm is controlled by a gyroscope/accelerometer. The gyroscope and accelerometer were merged to find the precise angular position of an object. An artificial intelligence algorithm was used to assess the head gesture data and train the arm. The result would be human head movement and the robotic prosthesis moving parallel in synchronization. The algorithms were developed on an Arduino Uno with the MPU-6050 IMU board. The MPU-6050 combines a 3-axis gyroscope and a 3-axis accelerometer together with a Digital Motion Processors. The gyroscope has a full scale range of ±250, ±500, ±1000, and ±2000°/sec dps (degrees per second) and the accelerometer with ±2g, ±4g, ±8g, and ±16g. The MPU-6050 is placed on the MUSE headset. Head movements were detected through the sensor in terms of acceleration and angles, corresponding to the arm's speed and tilts. Combining gyroscope and accelerometer data allowed us to calculate the angle with respect to a specific axis. The gyroscope picks up head gesture data and communicates with the main Arduino board. The data received by the Arduino is processed through the artificial intelligent algorithms, with the output being commands sent to servo motors for movement.

To process the raw data, various libraries and geometrical calculations were used to decipher exact angles of gestures. The Kalman filter was used to recalculate angles and compare with world frames. The frame of the arm is on an (X,Y, Z) axis. The world frame was considered ideal, and sensor displacement was calculated along the (X,Y,Z) axis, with the servo angle calculated. The prosthesis moves along the X,Y, and Z axis. Each motor is confined to its specific rotation, a y-axis motor can only perform y-axis rotations. The arm is made up of 6 servo motors with 2 for each axis, each controlling 180 degrees of movement which are defined to their axis rotation. To find the displacement angle of the human hand, geometrical calculations would be used to transform the raw values of the sensor. The force sensitive resistors are used in a closed loop feedback system on the Arduino using various algorithms.

Results

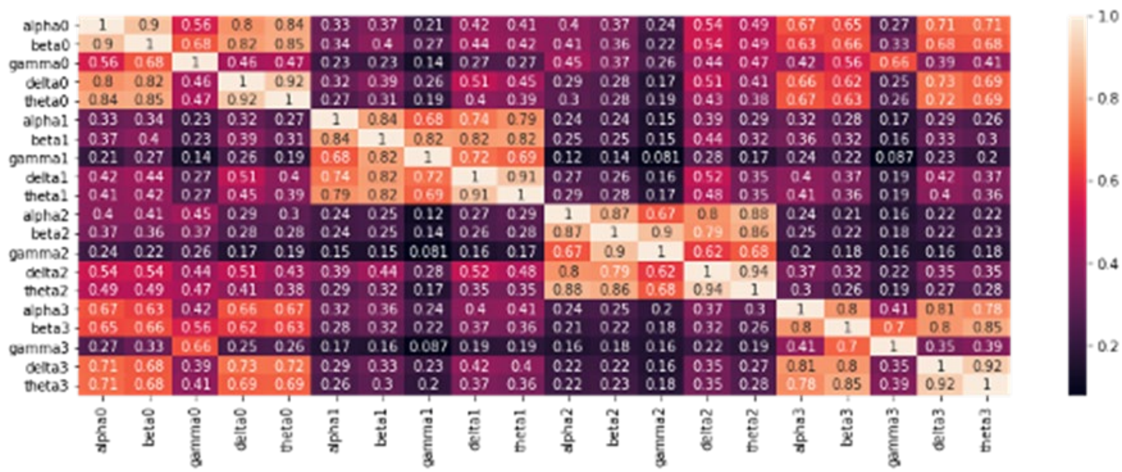

Figure 4. Variation of brain waves in the data set

The novel EEG decoding system boasts an accuracy of 94.7% which is considered an industry leading standard (Bhuyan, 2014). The figure below demonstrates the training algorithm's ability to decipher spikes in attention utilizing beta wave detection from the 30 CSV files. After multiple training trials the accuracy reached 100% for all beta waves of varying frequencies; 13 Hz, 24 Hz, and 30 Hz were used as they are part of the range of frequencies of beta waves. The graph shows the results for the various beta waves, to confirm accuracy of all possible detections. Beta waves frequency band was used since it contains the most relevant information for BCI applications. It also has the most variability which is necessary to identify the time period when the user enters a state of concentration.With the standard deviation at 5% there is low variability between test subjects, but this is likely to change with more data points and test subjects. The algorithm can be generalized to more people and additional data points for further research.

The overall cost of the arm comes down to $375 USD, which is 99.29% percent cheaper than what is currently available on the market. The use of 3D printing and PLA filament is what brought down most of the bill of materials. PLA filament is derived from renewable resources, and is known for its biocompatibility properties making PLA filament a good alternative.

		Weight (gr)	# Degrees of Freedom	# Actuators	Grasp speed (sec)	Cost in USD
Biological	Human Hand	400.00	22.00	35.00	0.23	
	SensorHand (OttoBock)	500.00	1.00	1.00		30,000.00
	i-limb Ultra Revolution (Touch Bionics)	504.00	6.00	5.00	1.20	100,000.00
	Bebionic (RSL Steeper)	539.00	6.00	6.00	1.90	11,000.00
Commercial	Michelin elo (OttoBock)	420.00	2.00	2.00		70,000.00
Average:		**472.60**	**7.40**		**1.11**	**52,750.00**
	Remedi	400.00	6.00	6.00		
	MANUS Hand	1,200.00	3.00	2.00	2.50	
	Smart EEG Hand (American Uni)	520.00	16.00	4.00	1.40	
	Fluid Hand 111	400.00	8.00	1.00	1.00	
	SoftHand Pro	520.00	2.00	2.00	1.50	
Research	X-Limb	253.00	13.00	5.00	1.30	N/A
Average:		**548.83**	**8.00**		**1.54**	
Total Average:		**514.18**	**7.72**		**1.37**	
Proposed	**Novel EEG Controlled Prototype Prosthetic Arm**	**450.67**	**4.00**	**4.00**	**0.58**	**375.00**

	Weight (gr)	# Degrees of Freedom	Grasp speed (sec)	Cost in USD
Improvement to Commerical Prosthetic Arm	4.64%	45.94%	47.74%	99.29%
Improvement to Research Robotic Arm	17.89%	50%	62.34%	N/A
Improvement to All Arms	12.35%	48.19%	57.66%	N/A

Figure.5. Breakdown of weight, degrees of freedom, actuators, grasp speed, and cost of prototype compared to current prosthetics in the market

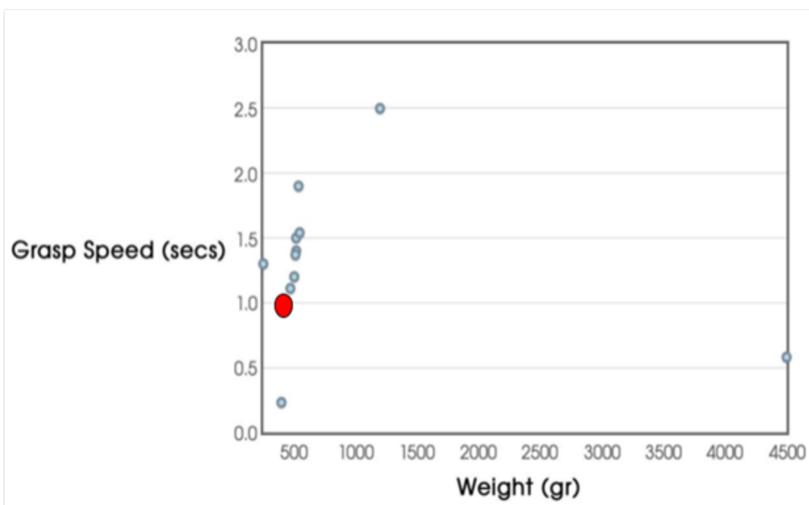

Figure 6. Scatterplot of weight and grasp speed of arm

Above is a comparison of the features of our proposed prosthesis prototype and others developed in commercial or research settings. Weight, degrees of freedom, actuators, grasp speed, and cost were all taken into account during this analysis. Our prosthetic has a high accuracy of function with a low bill of materials, ultimately lowering the manufacturing costs. This prosthetics proves high use in low resource areas, when proficiency is needed the most.

Discussion of Results

The final design was successful in achieving the objective of providing a full-fledged pipeline that applies techniques for data collecting, processing, analysis, and output evaluation, while also demonstrating its cost-effectiveness. The complete solution, for instance, makes it possible for a user to reasonably and accurately control a prosthetic device using inputs from their brain. The proposed approach achieves the basic goal despite the design difficulties that a real-time pipeline targeting frequently extremely noisy data can carry. We were able to create a functional prototype that could improve a disabled person's mobility by fusing the idea of mind-controlled open-close motion with the accuracy of EEG signal processing. Current state-of-the-art technologies continue to be priced high in the market (Maduri, 2022). Our research demonstrates the possibility of creating a low cost EEG-controlled prosthetic prototype that can serve millions of people in need, particularly those in underdeveloped communities without the means to afford the current market alternatives which are costly. Limitations of this prosthetic are related to the movement, as steps are being taken to make it smoother and more cohesive. Other low-cost, 3D printed prosthetics have used EMG signals, which utilize muscle sensors for motion. Further research can be performed to improve these mechanisms, integrating soft and hard limb properties, in an effort to bring a prototype to a fully commercialized and cutting edge go-to-market solution.

Acknowledgments

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References

Durham, Emily. “First-ever noninvasive mind-controlled robotic arm” *College of Engineering at Carnegie Mellon University*, 20 June 2019, engineering.cmu.edu/news-events/news/2019/06/20-he-sci-robotics.html. Accessed 23 Jan. 2023.

Meng, Jianjun. “Noninvasive Electroencephalogram Based Control of a Robotic Arm for Reach and Grasp Tasks” *Scientific Reports*, 14 Dec. 2016, www.nature.com/articles/srep38565. Accessed 23 Jan. 2023.

“Prosthetic arm Controller Based on Brainwaves Spectrum EEG Sensor” IOPscience, iopscience.iop.org/article/10.1088/1757-899X/662/5/052017. Accessed 23 Jan. 2023.

www.astesj.com/publications/www.astesj.com/publications/ASTESJ_0203111.pdf. Accessed 23 Jan. 2023.

Lebedev, Mikhail A. “Electroencephalogram-Based Brain–Computer Interface and Lower-Limb Prosthesis Control: A Case Study”

Electroencephalogram-Based BrainComputer Interface,

www.frontiersin.org/articles/10.3389/fneur.2017.00696/full. Accessed 23 Jan. 2023.

ieeexplore.ieee.org/abstract/document/7746219. Accessed 23 Jan. 2023.

23 Jan. 2023, www.ncbi.nlm.nih.gov/pmc/articles/PMC6211123/. Accessed 23 Jan. 2023.

“ScienceDirect” www.sciencedirect.com/science/article/pii/S1877050917302454. Accessed 23 Jan. 2023.

https://www.uh.edu/news-events/stories/2015/March/0331BionicHand.php

“Ceeol” Article Detail, www.ceeol.com/search/article-detail?id=1030684. Accessed 23 Jan. 2023.

“Utilizing Deep Neural Networks for Brain–Computer Interface-Based Prosthesis Control
” digitalcommons.georgefox.edu/cgi/viewcontent.cgi?article=1027&context=eecs_fac. Accessed 23 Jan. 2023.

News, Neuroscience. “First-ever successful mind-controlled robotic arm without brain implants” *Neuroscience News*, 20 June 2019, neurosciencenews.com/bci-prosthetic-arm-14283/. Accessed 23 Jan. 2023.

Akhondi, H. (n.d.). *Similar articles in PubMed*. https://www.ncbi.nlm.nih.gov/books/NBK540962/

(n.d.). *Request Rejected*. https://ieeexplore.ieee.org/document/6991151