

Mind Wave Controlled Prosthetic ARM Without using Brain Implants



Abhinav Chinta, Mayank Mathur, Anisha M. Lal

Abstract: Every year, more than 1 million people undergo limb amputations, and nearly one in six of the world's population suffer from neurological disorders. Most of the afflicted are unable to perform basic day to day tasks. Until few years ago prosthetic arms served no actual utility to the one wearing it apart from giving an illusion of the limb, but now with the development of technology, prosthetic arms can be given utility to emulate the real functions of limbs. Using brain implants to read the brain signals, one can control prosthetic robotic arms which are fitted in place of the limbs. However, this procedure is invasive, risky and very expensive. Hence, not many people can afford this technology. Our paper attempts to shed light on a non-invasive cheaper approach to mind wave-controlled prosthetics without the use of brain implants. We have used an EEG headset to read the brainwaves allowing the user to move the robotic arm without having any implants. EEG headset is also a cheaper alternative to the expensive brain implants and it can be easily worn on the head and removed whenever needed. This allows us to help a wider demographic by proposing an affordable mind controlled prosthetic arm.

Keywords: BCI, EEG, Neural networks, P300, Robotic arm

I. INTRODUCTION

Nerve cells or neurons are connected to one another by dendrites and axons and are able to communicate by sending and receiving minute electrical signals. The patterns created during the interaction between the neurons are manifested as thoughts and emotional states. Distinguishable human thoughts generate unique patterns of electrical signals. Healthy people control limbs due to brain signals which are sent from the brain to the muscles of the body via the central nervous system. The muscles are able to decode the signals into physical movements. In fact, any sort of body movement requires precise communication between the brain and muscles. In the case of amputations, people are missing limbs and the electrical signals are rendered useless as they do not reach the destination muscles. However, in most cases the brain is still able to generate healthy brain signals for intended movements.

The problem exists only with the communication medium. In theory, if we could translate the brain signals using sensors, we could simulate the response. In neuroscience and neuro-engineering, electric signal activities of neurons are recorded with an electroencephalogram (EEG). This is done with a Brain Control Interface (BCI). The main purpose of a BCI is to detect brain activity in EEG and communicate the recorded activity to a computer or microcontroller where it is decoded. Essentially, a BCI allows people to send messages or control devices bypassing the brain's natural output pathways.

A BCI is a device that consists of an EEG—sensors that measure brain signals (often in the form of 'electrodes'), an amplifier that boosts the faint brain signals, and a computer which can translate the signals into actionable commands to control either computer programs or other devices (such as robotic prosthetics). The basic idea behind it is to translate user-produced patterns of brain activity into corresponding commands.

In addition to a signal acquisition module, a BCI also may consist of a signal processing module which includes pre-processing, feature extraction and classification. It is not necessary for BCI devices to house all of these modules; some may group several components into one algorithm or some may exclude the processing module altogether to cut computational costs. Most of the work we will be doing is associated with the processing of the brain signals meaning we would only require the signal processing module.

EEGs can be classified by 2 approaches: invasive and noninvasive. Invasive procedures require a surgery to insert the EEG sensor deep inside the scalp. On the other hand, noninvasive procedures simply require electrodes to be placed on the surface of the scalp. Non evasive BCIs are small, inexpensive easily fitted without any surgery. They can also be made portable and wearable. This flexibility has enabled BCI controlled devices to emerge extremely beneficial in the field of assistive technology in healthcare, especially for people with paralysis or amputations.

All these electrical waves will be sensed by a brain wave sensor and it will convert the data into packets and transmitted through Bluetooth medium. A neural network will classify the signal to different classes, each class corresponding to an action. Then the action class will be transmitted to the microcontroller to trigger the respective movement. With this, we can map human thoughts to mechanical actions and hence control the robotic arm.

In our approach, we have used a P300 based BCI. P300 brain signals are a positive potential deflection in the on-going brain activity at a latency of around 300ms after the stimulus response.

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P300 waves have a number of desirable qualities that aid in implementation; P300 waves correspond to the physical response of the stimulus rather than to the stimulus itself which makes the waveform consistently measurable to elicit specific response. The P300 waveform can also be consistently evoked in almost all subjects with little variation in measurement techniques, which helps to simplify interface designs and allows greater accessibility and usability.

II. LITERATURE REVIEW

The practicability of forming a direct communication channel between the human brain and computers or robots has been a topic of scientific conjecture and even science fiction for a long time. Over the past twenty years, this idea has been gaining traction due to a large number of R&D programs, and has evolved into one of the fastest-growing fields of scientific research. BCI technology, by providing a new, artificial output channel the human brain to communicate or control external devices, has brought forth numerous clinical applications such as restoration of motor control in the form of, say, a robotic prosthetic limb. This is the aspect of BCI application we will be exploring in this paper. Other applications include environmental control—in which bedridden users can control the settings of the room environment (e.g. room temperature, fan speed, lights, TV etc.), locomotion—which allows users to steer wheelchairs by simply thinking about the direction they would like to travel, and even neurohabilitation—which aims to aid recovery from a nervous system injury by serving as therapeutic tools to help users relearn basic motor functions. Potential users for such technology can be classified into two groups. First group includes people lacking from neuromuscular control suffering from neurological disorders such as ALS, cerebral palsy, brainstem stroke or spinal cord injuries. The second group includes individuals possessing neuromuscular control but missing the output muscles due to limb loss.

BCI devices can be categorized by the specific electrophysiological features measured. In recent years, three types of EEG-based BCI devices have been developed and tested for the purpose of communication, specifically those based on: 1) slow cortical potentials (SCPs); 2) P300 potentials; and 3) sensorimotor rhythms (SMRs). Both the SCP BCI and the SMR BCI have a steep learning curve and require significant training for the users to gain a sufficient control of their brain activity to produce signals that can be effectively classified for application purposes. In contrast, P300 potential waves convey the brain's response to stimuli (visual or auditory) and requires minimal user training. For this reason, we have decided that a P300 BCI would be a viable option.

Most modern approaches for BCI controlled prosthetic involve 3 steps:

1. **Signal Acquisition:** This step involves detection and measurement of the neurophysiologic state of the brain. The recording interface (electrodes placed beneath the skull and over the cortical surface) of the BCI tracks brain wave activity reflecting a person's intent of movement.
2. **Feature Extraction:** Brain signals contain a vast amount of data and it is important to extract only the signal features which encode the intent of user. In this paper,

we will be exploring the utility of P300 potential amplitudes as the signal feature.

3. **Feature Translation:** The third step involves translating the extracted feature signals into device readable instructions. Most approaches, use a simple classification rule to determine the required command, based on a predefined mapping. However, this does not accommodate the subtle inconsistencies and nuances involved with brain signals. Furthermore, the edge cases might vary from person to person. Due to these reasons, the accuracy is limited. We attempt to circumvent this problem by using a neural network trained on a user's own brain signals. Though this may take time, it is better to train a classification model to correctly translate brain wave data rather than training the user itself to think in a specific way to elicit a particular brain wave pattern. With sufficient training data, the accuracy of a neural network can reach higher than 90%.
4. **Device Output:** Involves converting the actionable instructions into physical movements executed by an external device. We will be exploring the use of robotic prosthetics for amputees or individuals with neurological system disorders.

III. SYSTEM DESIGN AND SPECIFICATIONS

For our proof of concept, we have used an EEG headset called Neurosky Mobile 2. The headset is Bluetooth capable and transmits brainwave data with negligible latency. The EEG data is transmitted to a processor which uses neural networks to determine intent of thought and sends the command to the prosthetic arm to perform the required hand movement.

A. SYSTEM ARCHITECTURE

The model consists of 3 modules out of which one is software module, one is a mechanical module and one is an electric module. This is a generalized architecture which can be modified according to required use case.

1. **EEG Module:** Consists of the BCI headset and is responsible for detecting the P300 waves and sending the serial data to the processing unit. Any open source headset can be used as long as the latency and accuracy are limited to reasonable amounts.
2. **Control Module:** The software-based processing unit which translates the raw EEG serial data pertaining to a particular thought to the physical action like lifting of arm, gripping an object etc. This is done using a Long Short-Term Memory Neural Network which, in our implementation, we have trained using a custom prepared dataset.
3. **Robotic Arm:** This is the physical motorized robotic arm which will contain the exoskeleton and the actuators required to move the various parts of the arm to emulate real arm movements. Actuators may include various servo motors for precise movement. A microcontroller is used to control all the motors in the arm.

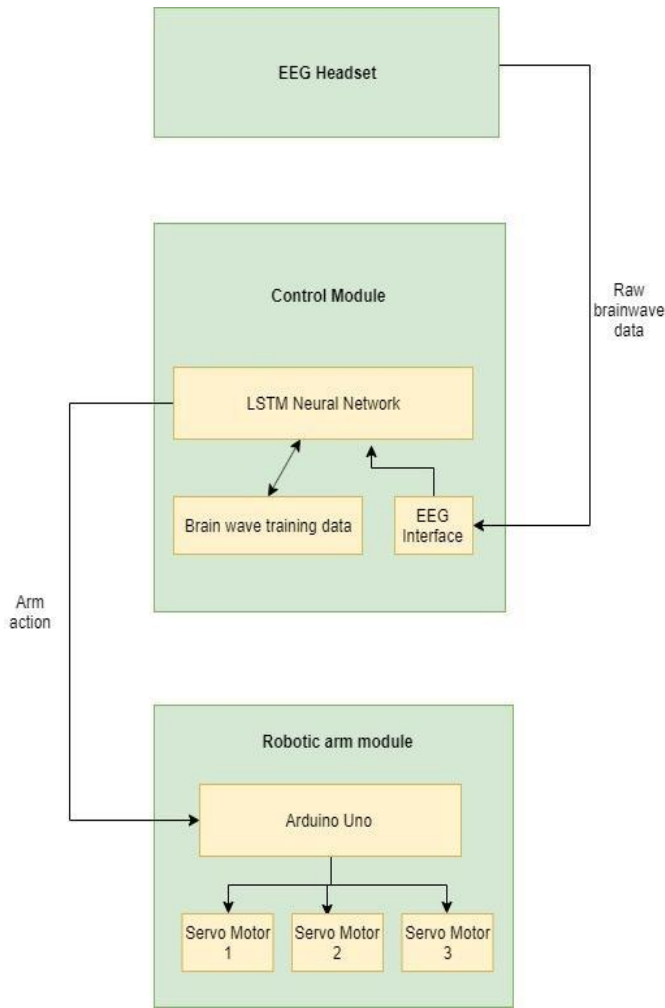


Fig 1. System Architecture Diagram

B. DATA COLLECTION

In our implementation, we have trained a neural network for the task of feature translation. For this purpose, we generated a dataset by recording a test subject's P300 waves

elicited for a particular task. The Neurosky headset outputs the signal features in the form of high alpha, high beta, low alpha, low beta, low gamma, mid gamma and theta waves. All of these individual waves are used as attributes for training our model.

In order to find the right interval for recognizing an action we trained our model for wave pattern intervals of two to five seconds. The brain wave pattern of four seconds was found to be optimum to differentiate between different actions. We used a single test subject for collecting data for our dataset. For our dataset we were able to get total of 400 data entries. The test subject was asked to think of two polar opposite things (in this case it was yes or no) in order to get a clear distinction between the brain waves.

We suggest collecting the data over a period of time with the subject being in different physical and mental state to get a relatively more accurate model.

Figure 2 shows some of the collected sample data points, their attributes and required output. 0 implies upward arm movement and 1 implies downward arm movement.

a. C. CLASSIFICATION MODEL

For the classifier of brain waves we have trained an LSTM model. LSTM or Long Short-Term Memory models are a type of Recurrent Neural Networks (RNN). LSTMs are useful to classify, process and predict time series data even with time lags of unknown duration. This insensitivity to time series gaps gives LSTMs an advantage over alternative RNNs, hidden Markov models and other sequence learning methods. Therefore, LSTMs are a very promising solution to sequence and time series related problems.

Our model has been implemented in Python using Keras. The model consists of a LSTM input layer followed by 2 dense layers and output layer. After Training the model on 400 data points we were able to get an accuracy rate of roughly 62%.

	High alpha	High beta	low alpha	low beta	Low gamma	mid gamma	theta	Out
1	23472, 25133, 3384, 570	12029, 9678, 2976, 1584, 17621	17738, 135813, 6696, 18	11704, 21943, 1844, 3341, 9682	7887, 11693, 1501, 971	4878, 3100, 1350, 60	303257, 358700, 40084, 4950	0
2	2971, 6596, 6155, 2908	4746, 7097, 11261, 1768, 33945	13019, 23205, 37472, 6	5218, 19921, 10304, 3567, 21661	3302, 3825, 4527, 597	2032, 4110, 3560, 90	26763, 203055, 44159, 21156	1
3	4444, 1868, 35145, 272	1488, 1658, 8402, 4882, 9454	7576, 7638, 12740, 201	4397, 2603, 8078, 2883, 783	479, 1224, 4257, 937	390, 494, 8040, 850	183862, 26931, 58388, 9256	1
4	4417, 14929, 5955, 3319	1889, 14472, 14551, 15097, 1379	3639, 12901, 5135, 447	2081, 3610, 2296, 5991, 1840	3041, 4652, 2867, 6142	1109, 3806, 2493, 61	15362, 17794, 32449, 7305	1
5	2525, 5487, 17275, 944	8669, 2989, 7259, 10005, 9912	7899, 4885, 23054, 102	3490, 1711, 6074, 12277, 6688	4283, 1512, 4785, 3547	2218, 973, 5757, 299	8899, 19932, 149213, 7246	1
6	5041, 4975, 7025, 12030	7330, 3322, 10934, 2679, 2742	22364, 8938, 16833, 62	6062, 2208, 19553, 4469, 382	4213, 1200, 4909, 919	3047, 1363, 4934, 12	15656, 6888, 135162, 28316	0
7	3404, 3084, 12942, 136	1492, 1869, 4891, 2898, 8895	821, 3086, 919, 13339	1127, 1400, 4850, 1846, 11789	1795, 961, 13475, 3577	762, 495, 2964, 1645	4428, 36968, 4500, 8650, 339	1
8	634, 3372, 3014, 9225	713, 2935, 1713, 5541, 3367	3173, 5472, 3375, 5277	494, 10198, 6177, 3010, 3365	349, 3545, 1046, 5881	304, 2717, 572, 3687	9559, 5280, 26732, 34304, 11	1
9	5387, 6969, 3478, 5448	8077, 7222, 6955, 5293, 5766	4897, 5578, 9112, 2958	3589, 6090, 11588, 2312, 3141	5588, 7987, 4409, 8570	3083, 2310, 6876, 60	830, 473491, 17801, 7049, 39	1
10	1213, 11466, 4845, 5839	1687, 9058, 9214, 4907, 1857	1990, 7361, 3860, 4047	3561, 9322, 7079, 15090, 4628	1331, 4675, 2689, 5749	655, 4927, 5868, 459	44034, 92953, 18073, 19027	1
11	11965, 4815, 3805, 37390	2509, 3037, 7077, 9117, 9746	2232, 7358, 14252, 669	2911, 3276, 7652, 14755, 1809	1297, 1597, 6182, 5791	2921, 1790, 3264, 77	16040, 31299, 4014, 269519	0
12	11163, 9135, 4638, 9224	16157, 7517, 6836, 8558, 7320	11440, 34093, 8485, 209	9056, 23184, 5555, 20014, 13344	7232, 5116, 6566, 3618	4841, 3382, 3164, 32	78305, 372620, 15187, 29842	1
13	1960, 12830, 1634, 230	6221, 3672, 5178, 1822, 12977	4858, 28892, 137, 7610	2888, 4599, 8881, 5418, 2084	6194, 8280, 10396, 734	1714, 1928, 3145, 16	12962, 446429, 9391, 75280	1
14	3966, 12469, 1149, 4069	9318, 9738, 2968, 11351, 10180	3999, 24972, 9090, 2419	9870, 13904, 5070, 8947, 2174	6269, 3495, 2784, 5087	3032, 2373, 799, 440	8723, 308489, 38575, 279316	1
15	8358, 11368, 763, 2782	2897, 7528, 1191, 2702, 12544	4238, 11276, 468, 1312	1769, 4733, 875, 3508, 11736	1164, 3728, 140, 1760	1078, 3210, 247, 180	47156, 23461, 33428, 65924	1
16	2881, 3340, 3359, 5503	13256, 2334, 4781, 2635, 6426	3418, 8757, 2210, 2900	3919, 5064, 10368, 4681, 6264	13008, 1034, 5736, 159	4518, 2529, 2314, 61	13362, 25243, 4339, 49005, 7	1
17	3944, 4438, 23379, 487	6549, 2532, 17271, 3317, 5850	966, 13273, 41947, 5888	3562, 2386, 20617, 1980, 11749	4319, 736, 7219, 655	2572, 1107, 6536, 12	13007, 32488, 48704, 45672	0
18	5104, 1241, 2559, 1017	7401, 2220, 10585, 7979, 13151	5229, 5639, 9765, 1118	4438, 2121, 12717, 3009, 10322	2530, 1064, 6576, 3567	3667, 981, 4169, 258	4946, 29985, 13512, 3310, 61	0
19	5631, 6871, 14414, 2040	2756, 11630, 7923, 10051, 5332	7747, 7563, 3163, 75079	2407, 8195, 3368, 7333, 1972	2814, 8125, 9661, 4717	738, 7016, 6312, 461	55831, 30369, 11371, 126884	1
20	23460, 6127, 10092, 549	8578, 1843, 11639, 2398, 3635	13096, 1429, 3283, 1039	5747, 3520, 11781, 4071, 5805	8792, 835, 5745, 810	1362, 1214, 4813, 37	6890, 69245, 18993, 54676	1
21	8656, 3505, 8196, 4881	2875, 8648, 4445, 3232, 6384	10219, 2803, 37031, 238	3859, 12552, 16124, 2687, 14024	1710, 5204, 2241, 536	1586, 3520, 2493, 13	36514, 20750, 20576, 24562	1
22	3416, 763, 490, 12473	3463, 1230, 901, 14320, 3020	12483, 3292, 949, 1843	4744, 981, 1724, 6607, 5266	1460, 2419, 573, 5327	472, 912, 989, 4050	52070, 3912, 33957, 23542	2
23	3702, 5217, 1433, 17239	7981, 13742, 1187, 9850, 1605	21882, 29061, 6392, 117	4654, 15896, 2154, 10802, 3718	6384, 7022, 639, 3332	4078, 5812, 307, 347	14370, 36577, 26156, 16530	1
24	18899, 17306, 4440, 90	4702, 7324, 911, 1281, 11477	23259, 59158, 1817, 78	7098, 12746, 1256, 3185, 10038	1627, 5218, 1372, 1157	1230, 4830, 560, 569	83967, 151371, 3534, 26806	1
25	2979, 1713, 61811, 3419	3541, 3104, 8714, 2411, 7828	2553, 4122, 45216, 1069	4057, 4345, 14940, 3676, 11056	4122, 3242, 6473, 980	2688, 2313, 3000, 62	8563, 15278, 141406, 37824	1
26	851, 10733, 3093, 5062	7035, 11333, 3148, 2113, 1399	6057, 33333, 2083, 213	4533, 10137, 3398, 2446, 2763	5908, 4298, 2137, 1087	2180, 2873, 5321, 42	10719, 245115, 20014, 41635	0

IV. SYSTEM IMPLEMENTATION AND RESULT

The BCI unit consists of a Bluetooth capable EEG headset called Neurosky Mobile 2. This headset must be fitted on a

subject with the ear clip firmly clipped on the ear and the forehead electrode firmly pressed against the forehead.



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The electrical interfacing involves the motors, the power and the processing board. The motors are responsible for moving each of the joints present in the arm. The processing board makes up the software processing module, which receives the signals from the EEG device. It has the classifier running and based on the classification it sends signals to the motor to rotate. We have trained a LSTM neural network model to classify the brainwaves into actionable instructions. This module is housed in an intermediary computer interfaced between the BCI and robotic arm module.

For the output device, we have used a robotic arm. The arm is a gripper arm with joints to help rotation in the upward/downward direction. The arm is controlled by a microcontroller which decodes the instructions and executes physical movements (up and down).

V. CONCLUSION

Through the help of the EEG headset (Neurosky mobile 2) we are able to read the brain waves of the test patient and classify them using LSTM neural network. There is no latency when it comes to data collection but it takes four seconds to correctly classify the thought process. The model was trained and had an accuracy of 62%.

Although the results are sufficient for a basic demonstration in the form of a proof of concept, if this approach is to be used in real life, the accuracy of the model needs to be increased and the time required to classify the brainwaves needs to be reduced. For increasing the accuracy, a more sensitive equipment must be used to reduce the noise in recording the brainwaves. A larger dataset will help train a more accurate model. The arm in our POC model currently consists of a single gripper which provides limited functionality. For more realistic, real world functionality, a few more classes must be added to the model to assign various physical actions.

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