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EEG Controlled Exoskeleton

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***Abstract*— A physically paralyzed person is doomed to stay on a chair or the bed making him completely at mercy of a helper. To help these patients this device uses a Brain Computer Interface (BCI). A brain-computer interface (BCI) is a computer-based system that acquires brain signals, analyses them, and translates them into commands that are relayed to an output device to carry out a desired action. In principle, any type of brain signal could be used to control a BCI system. This device is an Exoskeleton made of steel/iron that will be attached the Patient who is Physically Paralyzed. An exoskeleton is the external skeleton that supports and protects an animal's body, in contrast to the internal skeleton (endoskeleton) of, for example, a human. It will give support to the Patient while standing up so that he/she doesn't fall down. The Brainwaves being read by the EEG will be fed to a neural networking model coded using Google's Tensor Flow which will create a model with a high enough accuracy to understand the intentions of the patient i.e. whether to stand up or not and the direction of movement. The Real-time data will be given to the existing model and the motors of the exoskeleton will move accordingly.**

***Keywords*— EEG-Electroencephalogram, NLP- Natural Language Processing, MLF- Multi Layered Feed Forward Network Neural, NN- Neural Networking, KAFO- Knee Ankle Foot Orthoses, PDE – Partial Differential Equation.**

I. INTRODUCTION

Previously paraplegics did not have many options other than using wheelchairs or crutches. Crutches can be extremely hard to use because the patients have to use their arms to carry their entire bodyweight and most likely they might not have enough muscle power for the task and even if they do they cannot walk around with crutches for a long time. These options though help the patient locomote, move from one place to another do not give all the Degrees of Freedom (DOF). Rather they do not give any Degrees of Freedom. The only allow the person to move by the machines themselves moving and not the person themselves. This exoskeleton will support to the body such that the patient can move themselves with help of the brain of plantation signals just like your legs.

The Exoskeleton will be anthropomorphically designed to allow the person to be completely at ease while wearing it. For this exoskeleton to move it requires an input which is given by the EEG headset which the patient must wear. This headset reads the brainwaves of the patient and sends it to the processor, Raspberry PI in this case. These brainwaves alone do not make any sense to the processor which controls the exoskeleton they have to be inferenced and converted into one of the four commands that the exoskeleton can perform.

This process of inference and conversion is done with the help of a Neural Network model. The Neural Networking model is a deep learning technique where the data points are taken from the EEG headset. These data points are then supplied to the model which makes an "educated" guess or prediction and outputs a label 0,1,2 or 3 for forward, back, left and right respectively.

This output then controls the motors and tells them the direction to move in order to move the exoskeleton forward or backward and thus the patient too.

II. THE EXOSKELETON

Exoskeletons were generally designed for creating load augmentation and rehabilitation systems. Medical exoskeletons are Medical electrical gear which is utilized to give portability to physically handicapped, harmed or frail people, who can't stroll because of an assortment of clinical reasons, for example, SCI, neurological disorders, major trauma like stroke, cerebral palsy, etc. Essentially, these kinds of exoskeletons are utilized in controlled conditions, for example, clinics and recovery centers under the management of clinical experts.

Medical exoskeletons are intended to support the joint/appendage movement of a patient in some particular way where functionality is restricted or lost as far as portability and quality. Medical exoskeletons for paraplegics are utilized to help patients endure a sort of paralysis as appeared in Fig. 1; paralysis is the inability in

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the sensory-motor functionality of the lower appendages forestalling ordinary movements, for example, standing and strolling. A few ordinary strategies have been utilized including braces and crutches, wheelchairs and orthotic gadgets. Braces and crutches neglect to give full movement autonomy to the individual and henceforth have restricted use. The method of motion through conventional aids, for example, wheelchairs has its own advantages and disadvantages as effectively expressed. Wheelchairs give successful development on level surfaces however cannot be utilized in close or unstructured territories and result in Excessive sitting in one stance. Additionally, wheelchairs don't allow eye-level interactions.

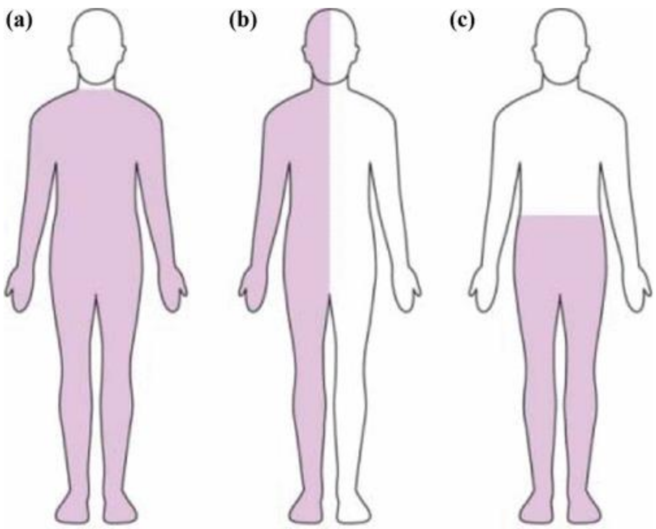

Fig 1. Types of Paraplegics where the colored portion is paralyzed. (a) Quadriplegia, (b) hemiplegia and (c) paraplegia.

All of the above problems can be addressed by the use of an exoskeleton. When designing the exoskeleton, some of the main features that need to be considered are:

- Shape: Presently, most designs for exoskeletons are unnatural in shape and are extremely uncomfortable and inefficient to use. Therefore, the design of the exoskeleton must be anthropomorphic.

- Information Exchange: Currently, there is a lack of direct information exchange between the human nervous system and the wearable robot (exoskeleton). The physiological state and desires of the user must be discerned and interpreted to originate motion intentions.

- Flexibility: The design of the exoskeleton must be flexible -the length of the thigh, shank and waist should be adjustable for more comfort and ease. For people with height from 1.60 m to 1.80 m, the average length variation of thigh and shank is about 6 cm. The shank length is about 0.246 times the stature and thigh length is about 0.245 times the stature.

- Degrees of Freedom (DOF): The exoskeleton must duplicate the freedom of movement of joints

- Characteristics: One of the most significant qualities the actuator of exoskeleton robot must have is a huge output power-to-weight proportion. Other significant qualities incorporate low inertia, quick reaction, high precision, and so forth.

Since an automated structure, for example, an exoskeleton contains a human part, the measure of collaboration the individual may have with it is legitimately identified with his level of impairment. A patient wearing an exoskeleton turns out to be a part of it, and the way the patient interfaces with such gadget must be considered as an indispensable piece of the entire framework. Since the ability of walk relies upon the level of weakness of the subject, exoskeletons are manufactured so they may work autonomously as segregated structures with auto balance instruments where the patient turns out to be just a traveler, or they can be worked as a complementary structure where the patient controls how the exoskeleton must carry on. We consider a patient having total leg weakness, with the end goal that solitary his mind can advise the exoskeleton to move around with a certain goal in mind.

III. EEG HEADSET AND SIGNAL ACQUISITION

A. Brainwaves and the different types of brainwaves

Gamma waves: Gamma waves are in the frequency scope of 31Hz and up. It is felt that it mirrors the mechanism of consciousness. Beta and gamma waves have been related with attention, perception, and cognition

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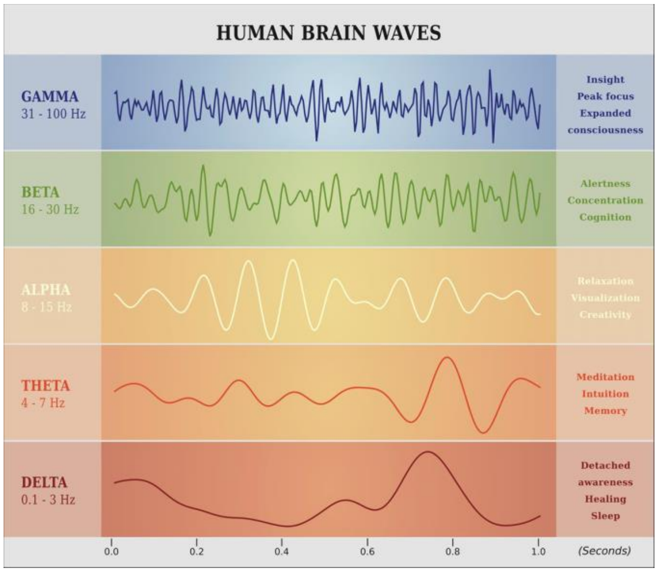

Fig 2. Different types of brainwaves

Beta waves: Beta waves are in the frequency scope of 12 and 30 Hz yet are frequently partitioned into β1 and β2 to get an increasingly explicit range. The waves are related with focused concentration and best characterized in central and frontal areas. Beta activity increases when an individual focuses on an assignment or discovers some new information

Alpha wave: Alpha waves, range from 7.5 to 12 Hz, they are related with relaxation and disengagement. Alpha waves happen during deep relaxation. Generally significant in the rear of the head and in the frontal lobe.

Theta wave: Theta waves, extend from 3.5 to 7.5 Hz, are connected to wastefulness, staring off into space, and the least influxes of theta speak to the scarcely discernible difference between being conscious or in a rest state. This emerges from emotional stress. It has additionally been related with creative inspiration and deep meditation.

Delta wave: Delta waves, extend from 0.5 to 3.5 Hz, happens when snoozing. Movement can prompt the production of fake delta waves, yet with an instant analysis (simply watching crude EEG records), this can be confirmed or unverified.

MU: is related with motor activities and is likewise found in the alpha wave frequency range, however where the maximum amplitude is recorded over motor cortex. So, it essentially enhances when there is an actual movement or when there is an intention to move

B. EEG Headset

Fig 3. EEG Neurosky Headset

The EEG Headset by Neurosky was used in this project. It consists of 2 electrodes, it reads the brainwaves of the patient via electrodes placed on the scalp of the patient. This EEG headset consists of a chip, *TGAM* which is the center of the brainwave detecting innovation technology. Together with dry electrodes, it detects the signs from the human cerebrum, sift through unessential noise and electrical impedance and converts to digital power.

C. EEG Signal Acquisition

The electrical action in the mind with which the neurons speak with one another is measure by EEG signals. The recording of the EEG signals is executed by fixing electrodes on explicit points regarding the subject's scalp where the brainwaves identified with movement and motor activities are all the more clear and intensified the standardized electrode placement scheme is referenced for the arrangement of the electrodes.

The signal noise which emerge because of muscular activities, flickering of eyes during signal acquisition procedure, and power line electrical noise will likewise be recorded when sign is being caught which will unfavorably influence useful features in the original signal. There are numerous techniques created to wipe out these undesirable signs.

The initial phase in activity is preprocessing which incorporates acquisition of signal after which we remove the noise to increase the signal's accuracy and afterward signal averaging which is a method which is expected to build the quality of a signal comparative with noise that is clouding it or to put in other words the noise that causes an antagonistic impact then thresholding the

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output, improvement of the subsequent signal, lastly, edge detection.

The second stage in the activity is extracting the features which is intended to decide a feature vector from a regular vector. A feature is an unmistakable measurement, basic segment extricated from a fragment of an example. Feature extraction process is intended to pick the features or data which is the most significant for classification exercise.

The signal stage is signal classification which can be solved by linear analysis, nonlinear analysis, adaptive algorithms, clustering and fuzzy techniques, and neural networks.

IV. NEURAL NETWORKS

A. Multi Layered Feed Forward Network

A MLF neural system comprises of neurons that are stacked into layers. The first layer is known as the input layer, the last layer is known as the output layer, and the layers between are hidden layers. Every neuron in each layer is associated with all neurons in the following layer. The association between the i^{th} and j^{th} neuron is described by the weight coefficient w_{ij} and the i^{th} neuron by the threshold coefficient v_i. The level of significance of the given association is dictated by the weight coefficient of a specific neuron's specific association with the following layer's neuron in the neural system.

For this Neural Network to make accurate predictions or output based on its inputs it has to be trained. Training the network refers to the updating of the weights which describes the association between the i^{th} and j^{th}. The process of updating is done by an algorithm known as the Backpropagation Algorithm.

B. Backpropagation Algorithm

The principle of the backpropagation approach is to model a given function by modifying the internal weights of input signals to produce an expected output signal. The framework is prepared utilizing a supervised learning method, where the error is determined utilizing the framework's output and a known expected output which is then introduced to the framework which is thus used to adjust its interior state.

BACKPROPOGATION FOR THE OUTPUT LAYER

So as to acquire the update rule:

$$\mathbf{u} \leftarrow \mathbf{u} - \eta \nabla_{\mathbf{u}} L(\mathbf{u})$$

How about we take a solitary weight uij . The partial derivative of the loss w.r.t. uij approaches:

$$\frac{\partial L}{\partial u_{ij}} = \frac{\partial L}{\partial y_j} \frac{\partial y_j}{\partial a_j^{(2)}} \frac{\partial a_j^{(2)}}{\partial u_{ij}}$$

Where i relates to the previous layer and j compares to the following layer. The partial derivatives were figured just adhering to the chain rule.

$$\frac{\partial L}{\partial y_j} = (y_j - t_j)$$

Following the L2-norm loss derivative.

$$\frac{\partial y_j}{\partial a_j^{(2)}} = \sigma(a_j^{(2)})(1 - \sigma(a_j^{(2)})) = y_j(1 - y_j)$$

Following the sigmoid derivative. Finally, the third partial derivative is the derivative of $a^{(2)} = hu + b^{(2)}$.

So,

$$\frac{\partial a_j^{(2)}}{\partial u_{ij}} = h_i$$

Replacing the partial derivatives in the expression above, we get:

$$\frac{\partial L}{\partial u_{ij}} = \frac{\partial L}{\partial y_j} \frac{\partial y_j}{\partial a_j^{(2)}} \frac{\partial a_j^{(2)}}{\partial u_{ij}} = (y_j - t_j) y_j (1 - y_j) h_i = \delta_j h_i$$

Therefore, the update rule for a single weight for the output layer is given by:

$$u_{ij} \leftarrow u_{ij} - \eta \delta_j h_i$$

BACKPROPOGATION FOR THE HIDDEN LAYER

Similarly to the backpropagation of the output layer, the update rule for a single weight, w_{ij} would depend on:

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$$\frac{\partial L}{\partial w_{ij}} = \frac{\partial L}{\partial h_j} \frac{\partial h_j}{\partial a_j^{(1)}} \frac{\partial a_j^{(1)}}{\partial w_{ij}}$$

adhering to the chain rule. Exploiting the outcomes we have so far for change utilizing the sigmoid activatio2n and the linear model, we get:

$$\frac{\partial h_j}{\partial a_j^{(1)}} = \sigma(a_j^{(1)})(1 - \sigma(a_j^{(1)})) = h_j(1 - h_j)$$

And

$$\frac{\partial a_j^{(1)}}{\partial w_{ij}} = x_i$$

The solution for weight w_{11} below.

$$\frac{\partial L}{\partial h_1} = \frac{\partial L}{\partial y_1} \frac{\partial y_1}{\partial a_1^{(2)}} \frac{\partial a_1^{(2)}}{\partial h_1} + \frac{\partial L}{\partial y_2} \frac{\partial y_2}{\partial a_2^{(2)}} \frac{\partial a_2^{(2)}}{\partial h_1} =$$
$$= (y_1 - t_1)y_1(1 - y_1)u_{11} + (y_2 - t_2)y_2(1 - y_2)u_{12}$$

From here, we can calculate

$$\frac{\partial L}{\partial w_{11}}$$

Which was what we wanted. The final expression is:

$$\frac{\partial L}{\partial w_{11}} = [(y_1 - t_1)y_1(1 - y_1)u_{11} + (y_2 - t_2)y_2(1 - y_2)u_{12}]\, h_1(1 - h_1)x_1$$

The generalized form of this equation is:

$$\frac{\partial L}{\partial w_{ij}} = \sum_k (y_k - t_k)y_k(1 - y_k)u_{jk}h_j(1 - h_j)x_i$$

BACKPROPOGATION GENERALIZED

Utilizing the outcomes for backpropagation for the output layer and the hidden layer, we can assemble them in one equation, summing up backpropagation, within the sight of L2-norm loss and sigmoid activations.

$$\frac{\partial L}{\partial w_{ij}} = \delta_j x_i$$

where for a hidden layer

$$\delta_j = \sum_k \delta_k w_{jk} y_j (1 - y_j) x_i$$

Technically, the backpropagation algorithm is a strategy for training the weights in a multilayer feed-forward neural network.

V. Working of the Project

A. Neural Networking Model

We used a sequential Neural Networking model by using the keras. Sequential class. It creates a sequentially stacked layers. We use 1 input and 1 output layer, with 2 hidden layers each with a ReLu activation function excluding the output layer which uses a Sigmoid Function. We use a model with an adam optimizer to get an accuracy of 90.12%.

B. Servo Motors and the Exoskeleton

The predicted label controls how and which motor moves i.e. to mimic the human body there are 4 motors fit. 2 on each leg. One for the movement of the hip joint and the other for the movement of the knee joint. The exoskeleton has been 3D printed using PLA plastic. It supports the patient with straps around his thigh and calf so that exoskeleton doesn’t come off while moving.

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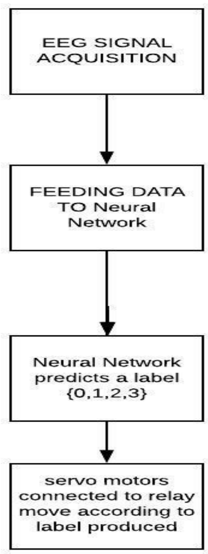

Fig 4. Block Diagram

Fig. 5. The exoskeleton

VI. CONCLUSION

A brain-computer interface (BCI) is a computer-based system that acquires brain signals, analyses them, and translates them into commands that are relayed to an output device to carry out a desired action. In principle, any type of brain signal could be used to control a BCI system. The Brainwaves being read by the EEG will be fed to a neural networking model coded using Google's Tensor Flow which will create a model with a high enough accuracy to understand the intentions of the patient i.e. whether to stand up or not and the direction of movement.

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