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Artificial Muscle Intelligence System With Deep Learning for Post-Stroke Assistance and Rehabilitation

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ABSTRACT Stroke is one of the prime reasons for paralysis throughout the world caused due to impaired nervous system and resulting in disability to move the affected body parts. Rehabilitation is the natural remedy for recovering from paralysis and enhancing the quality of life. Brain Computer Interface (BCI) controlled assistive technology is the new paradigm, providing assistance and rehabilitation for the paralysed. But, most of these devices are error prone and also hard to get continuous control because of the dynamic nature of the brain signals. Moreover, existing devices like exoskeletons brings additional burden on the patient and the caregivers and also results in mental fatigue and frustration. To solve these issues Artificial Muscle Intelligence with Deep Learning (AMIDL) system is proposed in this paper. AMIDL integrates user intentions with artificial muscle movements in an efficient way to improve the performance. Human thoughts captured using Electroencephalogram (EEG) sensors are transformed into body movements, by utilising microcontroller and Transcutaneous Electrical Nerve Stimulation (TENS) device. EEG signals are subjected to pre-processing, feature extraction and classification, before being passed on to the affected body part. The received EEG signal is correlated with the recorded artificial muscle movements. If the captured EEG signal falls below the desired level, the affected body part will be stimulated by the recorded artificial muscle movements. The system also provides a feature for communicating human intentions as alert message to caregivers, in case of emergency situations. This is achieved by offline training of specific gesture and online gesture recognition algorithm. The recognised gesture is transformed into speech, thus enabling the paralysed to express their feelings to the relatives or friends. Experiments were carried out with the aid of healthy and paralysed subjects. The AMIDL system helped to reduce mental fatigue, miss-operation, frustration and provided continuous control. The thrust of lifting the exoskeleton is also reduced by using light weight wireless electrodes. The proposed system will be a great communication aid for paralysed to express their thoughts and feelings with dear and near ones, thereby enhancing the quality of life.

INDEX TERMS Artificial muscle intelligence, assistivetechnologies, BCI, EEG, exoskeleton, healthcare, intelligent solutions, deep learning system, paralyzed, stroke.

I. INTRODUCTION

The recent survey by reeve foundation revealed the impact of paralysis on world population, affecting approximately 5.4 million people [1], [2]. The survey also identified stroke (33.7%) as the major cause for paralysis. Paralysis is the deficiency of brain to activate muscle function of any body part. Paralyzed persons find it difficult to perform their routine activities without assistance. Rehabilitation is one of the natural ways of healing paralysis. Because of this there is increasing interest and involvement in the field of post stroke rehabilitation. Exoskeleton-assisted technologies have emerged as a reliable means for rehabilitation of the affected upper and lower limbs [3]. Exoskeleton movements were controlled using sensors like gyroscopes, accelerometers, and potentiometers. Recently the focus is on controlling

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exoskeleton using Brain Computer Interface (BCI) [4]. Antelis *et al.* demonstrated upper limb movement of the paralyzed using EEG signals [5]. A closed loop is established between human thought and movement of paralyzed limb using non-invasive BCI [6]. Android feedback based BCI training is employed to enhance brain rhythms during motor imagery task. The realistic feedback is realized in training session using humanoid robot [7]. Humanoid robot is navigated in real-time indoor environment based on human intentions. The asynchronous BCI system was designed using two level classifiers [8]. Co-operation and co-ordination of dual robotic arm is demonstrated using EEG based system. SSVEP (Steady-State Visual Evoked Potentials) are utilized to improve the user concentration level [9]. Electromyography (EMG) sensors are also used to control exoskeleton movements, EMG returns the information regarding human muscular activity [10]. The motor adaptability of upper limb is predicted using resting state functional connectivity. The system could identify effectiveness of robotic upper limb rehabilitation in different patients [11]. However, the system does not investigate real time human behaviors and thoughts. The clinical trials to investigate the effectiveness of BCI training sessions on stroke patients with upper limb paralysis are carried out. The results of the trial indicate that BCI based assistive devices are effective for post stroke rehabilitation [12]. Human intentions measured through cortical potentials were used to control upper-limb exoskeleton movements. The BMI system eliminated the need for recalibration but resulted in large false positive rates [13]. Grasping feature is incorporated into the assistive device for amputees using non-invasive EEG control. The participants were able to grasp the objects, but resulted in low success rate without sufficient training [14]. Brain activity is modulated to control robotic arm with multiple degrees of freedom. The system demonstrated the effective control of robotic arm with few training sessions, but increased the latency periods during certain operations [15]. Hybrid BMI system based on sensorimotor cortical desynchronization (ERD) and electromyography (EMG) activity was designed to control upper limb movements. The integration of BMI, NMES and exoskeleton improved the system accuracy, but increased the system complexity [16]. The linear control of upper limb is demonstrated using motor imagery based BCI and Functional Electrical Stimulation (FES), support is provided to the arm using passive exoskeleton. The generated limb movement is evaluated to identify the precise positioning [17]. The self-induced EEG variations based on ERD/ERS is utilized for controlling upper limb movements. Distinguishable patterns are obtained for left and right-hand movements in both motor imagery and motor execution experiments [18]. Online robot control using motor imagery based BCI is designed with high classification accuracy. The mental imagination of hand movement is detected for controlling the robot movements [19]. An integrated platform consisting of BCI controlled exoskeleton, functional electric stimulation (FES) with proprioceptive feedback is developed. Goal directed motor task is used for training and subjects could complete the task with minimum latency period [20].

In our previous works [21]–[23], we have demonstrated an alternative technology to exoskeletons using non-invasive brain signals. Also, exoskeletons with feedback mechanism has also been implemented by us [22]. The paralyzed body part is stimulated using Transcutaneous Electrical Nerve Stimulation (TENS) device and Microcontroller [24]. Because of the dynamic and uncertain nature of brain signals, most of the BCI systems result in miss-operation, mental fatigue and it is hard to produce continuous control. The proposed system is designed to address the above gaps in research.

AMIDL is designed to reduce miss-operation, user fatigue and to enhance user capabilities. In the proposed work, human intentions are monitored in real-time employing 16 channel EEG sensors. TENS machine is integrated with Muscle Inspired Algorithm (MIA) to produce movements on the upper limb. Subjects are relieved from the task of carrying exoskeleton structure. The system is designed to perform six different movements on the affected upper limb. The different hand postures used to trigger the rehabilitation process are Release, Grasp, Rollup, Roll down, Rollup Release and Rollup grab. In the offline phase, Artificial Muscle movements corresponding to each posture are recorded to create the database. The decoded EEG signals are transformed into muscle activation signals in real-time environment. The captured EEG signal is converted into frequency domain using Walsh Hadamard Transform (WHT) for feature extraction. The extracted features along with WHT coefficients are utilized for the classification of different limb movements. The activation signal is then correlated with the recorded muscle movements. The signal with superior characteristics is passed on to the upper limb electrodes for inducing motion. In case of ambiguity or inadequate EEG signal, the periodic activation of the affected body part will be taken care by the artificial muscle movements. If the activation is executed by brain signal, the produced gesture is recognized and passed on to the care giver as voice command. Thus, AMIDL transforms human thoughts into different movements on the unique upper limb structure. The EEG activated movements are utilized for communicating paralyzed person's emergency need to the caregivers.

The contributions of our research are,

- An Artificial Muscle Intelligence with Deep Learning (AMIDL) system without exoskeleton structure, in which movements of paralyzed body part is controlled based on user intentions.
- An adaptive mechanism based on recorded muscle movements is integrated with the system to enhance continuous control and facilitate rehabilitation.
- Designed flexible assembly, which can be customized according to the degree of disability.
- Communication aid is incorporated in the system using gesture recognition

- The subject concentration is improved by using multimedia feed back

The rest of the paper is organized into four sections in which section 2 describes different existing methods used in BCI controlled upper limb movements.

II. RELATED WORKS

In this section, we discuss few existing devices controlled by Brain-Computer Interface designed specifically for paralyzed people. But the problem with most of them is that the users are unable to get continuous control over the device. The users are required to have high level of concentration to get sufficient control on the device, which results in mental fatigue and frustration. Additionally, there is no arrangement to take care of the miss-operations. The subjects are also burdened with the task of carrying the load of exoskeleton on the affected body parts. Our research focus on overcoming these major problems and provides an efficient and flexible solution, which can enhance the post stroke recovery process. Our system also provides a communication aid for the paralyzed to express their feelings.

The assistive rehabilitation devices and its EEG control techniques are systematically reviewed and the major gaps are identified [25]. Three-dimensional robotic assistance using motor imagery task for upper limb rehabilitation is demonstrated with multi-joint exoskeleton. Desynchronization of sensorimotor oscillations in the β-band is measured to control the different robotic hand movements [26]. Different upper limb exoskeletons like Track hold [27] and Armeospring [28] are employed to track upper limb movements. Both these devices have integrated passive robots with virtual reality environment to help patients carry out their daily routine activities. Control of assistive robots are improved by integrating electroencephalography (EEG) and electrooculography (EOG). This hybrid approach called as brain/neural-computer interaction (BNCI) is adopted to control grasping movements of a hand exoskeleton [29]. Multimodal signal approach is further used to enhance control system for external device connected to the upper limb. EEG and EMG signals are integrated to improve the classification accuracy and to reduce the false positive rate [30]. Upper limb robotic orthosis, FES, and wireless BCI are combined in an efficient way on account of EEG signals. EMOTIV EEG device is employed to measure EEG signal, which is used to control grasp/release of an object [31]. An integrated passive robotic system is developed for assisting the paralyzed. The system employs a robotic device which compensates gravitational effects to allow exercise, virtual engines to facilitate interaction and EEG to monitor brain activities. The three components are coordinated in real-time to enhance the rehabilitation process [32]. The effects of BCI therapy on post stroke rehabilitation is analyzed based on motor imagery tasks. The analysis is performed by measuring coherence of EEG in different regions of the brain and the best result for motor recovery is obtained for the activation of lesion hemisphere [33]. The online BCI coupled with hand exoskeleton is employed to address the issues related to proprioceptive feedback on the regulation of cortical oscillations. The results show an enhancement in SMR desynchronization with proprioceptive feedback during flexing and extending fingers of the exoskeleton [34]. Multimodal architecture based on BCI, exoskeleton and an active vision system is proposed to enhance BCI control and rehabilitation process. The VR environment coupled with bio feedback help to reduce mental fatigue and improve user interactions [35]. Few studies have also been conducted in related areas recently [36]–[42] Al-Turjman *et al.* proposed another interesting system using optimal haptic communications [43]. Xu *et al.* [44] proposed a three-dimensional animation to guide upper limb movements using EEG signals. Feature extraction is carried out by Harmonic Wavelet Transform (HWT) and linear discriminant analysis (LDA) classifier was utilized to classify the patterns for controlling the upper limb movements. MR-compatible robotic glove operates pneumatically and doesn't cause any disturbance to functional Magnetic Resonance imaging (fMRI) images during rehabilitation process [45]. The resistance to mechanically actuated movements in exoskeleton robot is measured based on spasticity. The relevant guidelines for practical neuro-rehabilitation robot design based on degree of spasticity and resistance is established [46]. In most of the design it is hard to get continuous control on the exoskeleton due to the non-stationary nature of the EEG signal. Moreover, the subjects experience metal fatigue and frustration due to lack of superior control. None of the device in the literature focused on providing communication aid for the paralyzed. Our research focus on solving these issues in an efficient manner using AMIDL system proposed in this paper. Table 1 shows the comparisons between AMIDL and existing systems in the literature.

III. MATHEMATICAL MODEL

This section presents and discusses the mathematical modelling of the proposed system. The system is designed to perform six different movements on the affected upper limb. The different hand postures used to trigger the rehabilitation process are Release, Grasp, Rollup, Roll down, Rollup Release and Rollup grab. In the offline phase, Artificial Muscle movements corresponding to each posture are recorded to create the database. The decoded EEG signals are transformed into muscle activation signals in real-time environment.

In Hand Posture Release operation, the voltage and current applied to electrodes are assumed as V_{H-P-R} & I_{H-P-R}. Similarly, the voltage and current applied to electrodes in the other postures are defined as,

Hand Posture Release → V_{H-P-R} I_{H-P-R}
Hand Posture Grasp → V_{H-P-G} I_{H-P-G}
Hand Posture Roll up → V_{H-P-Ru} I_{H-P-Ru}
Hand Posture Roll down → V_{H-P-Rd} I_{H-P-Rd}
Hand Posture Role up Release → $V_{H-P-R-R}$ $I_{H-P-R-R}$
Hand Posture Roll up Grasp → $V_{H-P-R-G}$ $I_{H-P-R-G}$

The voltage for Hand Posture Release, $V_{H-P-R} \neq$ Hand Posture Grasp, V_{H-P-G}. If they are same the hand posture

TABLE 1. AMIDL comparisons with existing system (Sorted by success rate).

METHOD REFERENCE NO., YEAR	NO. OF SUBJECTS	TYPE OF CONTROL	TYPE OF EEG SIGNAL	DEVICE ASSIGNED	TASK	ACCURACY/ SUCCESS RATE
Ref [14], 2016	2 amputees	EEG -based control	Motor imagery Low frequency-time domain feature	Prosthetic hand	Grasping objects	63.6%
Ref [15], 2016	13 healthy subjects	EEG-based control	ERD/ERS	Arm exoskeleton	Reach and grasp tasks	77.8%
Ref [12], 2017	64 stroke patients	EEG-based control	Motor imagery 5–30 Hz EEG signal	Hand exoskeleton	Hand open/closed	79.4%
Ref [17], 2016	7 healthy subjects	EEG-based control	7–30 Hz EEG signal	ArmeoSpring and FES	left hand, right hand, and feet	79.6%
Ref [16], 2016	7 stroke patients	EEG-based control	ERD	ArmeoSpring exoskeleton	Wrist extensor/flexor	80.7%
Ref [13], 2016	3 chronic stroke patients	EEG-based control	MRCPs	MAHI exoskeleton	Elbow flexion/extension	81.3%
Ref [11], 2018	19 healthy subjects	EEG-based control	15–25 Hz EEG signals	Robotic Arm	Upper limb movement/reaching	83.5%
Ref [18], 2016	4 healthy subjects	EEG-based control	ERD/ERS	Custom upper limb exoskeleton	Left/right hand and left hand versus both feet	84.29%
Proposed System, AMIDL	20 subjects	EEG and EMG based control	Motor Imagery ERD/ERS with multimedia feed back	TENS device with EMG Electrodes	left or right hand movements	87%

will be stable. If $V_{H-P-R} > V_{H-P-G}$, then Hand Posture Release will be activated compared to Hand Posture Grasp.

The other parameters in the system is defined as follows. The diameter of EEG electrode is D_E. The scalp resistance is S_R. The conductivity of the EEG electrodes depends upon the multiplying factor is assumed as 'T'.

When the multiplying factor 'T' is more, the conductivity will be more & vice versa. The multiplying factor depends on the positioning of EEG electrodes, the diameter of EEG electrodes and scalp resistance.

The V_{H-P-T} denotes the Hand Posture Threshold. The threshold varies depending on the different types of postures.

A. THE POSTER ACTIVATION REGION

The Hand Posture Current in the system is given by,

$$I_{H-P} = \frac{D_E}{S_R}\int_{V_{H-P-inital}}^{V_{H-P-final}} T\left(E_Q\right) dV_{initial-final} \tag{1}$$

For the condition from Hand Posture Grasp to Hand Posture Release with the Hand Posture Threshold acting as an intermediate, the Hand Posture Release current is given by,

$$IH-P-R = \frac{D_E}{S_R}\int_{V_{H-P-G}}^{V_{H-P-R}} T\left(E_Q\right) dVR-G \tag{2}$$

where E_Q is the net potential to EEG electrodes. Also, we have,

$$E_Q = V_{H-P-R} - V_{H-P-T} - V_{H-P-G} \tag{3}$$

If E_Q is positive then, V_{H-P-R} is dominating V_{H-P-T}& V_{H-P-G}. The reguired potential to EEG electrodes will be analyzed and the Hand Posture Release operations will be performed.

For $V_{H-P-G} < V_{H-P-T} \leq V_{H-P-R}$, neglecting the surrounding areas of EEG electrodes and conductive loss. The hand posture for release will be activated as,

$$I_{H-P-R} = V_{H-P}\left(V_{H-P-G}, V_{H-P-R}\right) \tag{4}$$

Similar relation can be developed for the remaining postures.

If the movement is a combination of different postures, say Roll up and Release, then,

Let say the initial posture is in grasp stage,

$$\begin{aligned} I_{H-P-R-R} &= \frac{D_E T}{S_R}\left\{\int_{V_{H-P-G}}^{V_{H-P-Ru}} (V_{H-P-Ru} - V_{H-P-T} - V_{H-P-G})\, dV_{G-Ru}\right. \\ &\quad \left. + \int_{V_{H-P-Ru}}^{V_{H-P-R}} (V_{H-P-R} - V_{H-P-T} - V_{H-P-Ru})\, dV_{Ru-R}\right\} \end{aligned} \tag{5}$$

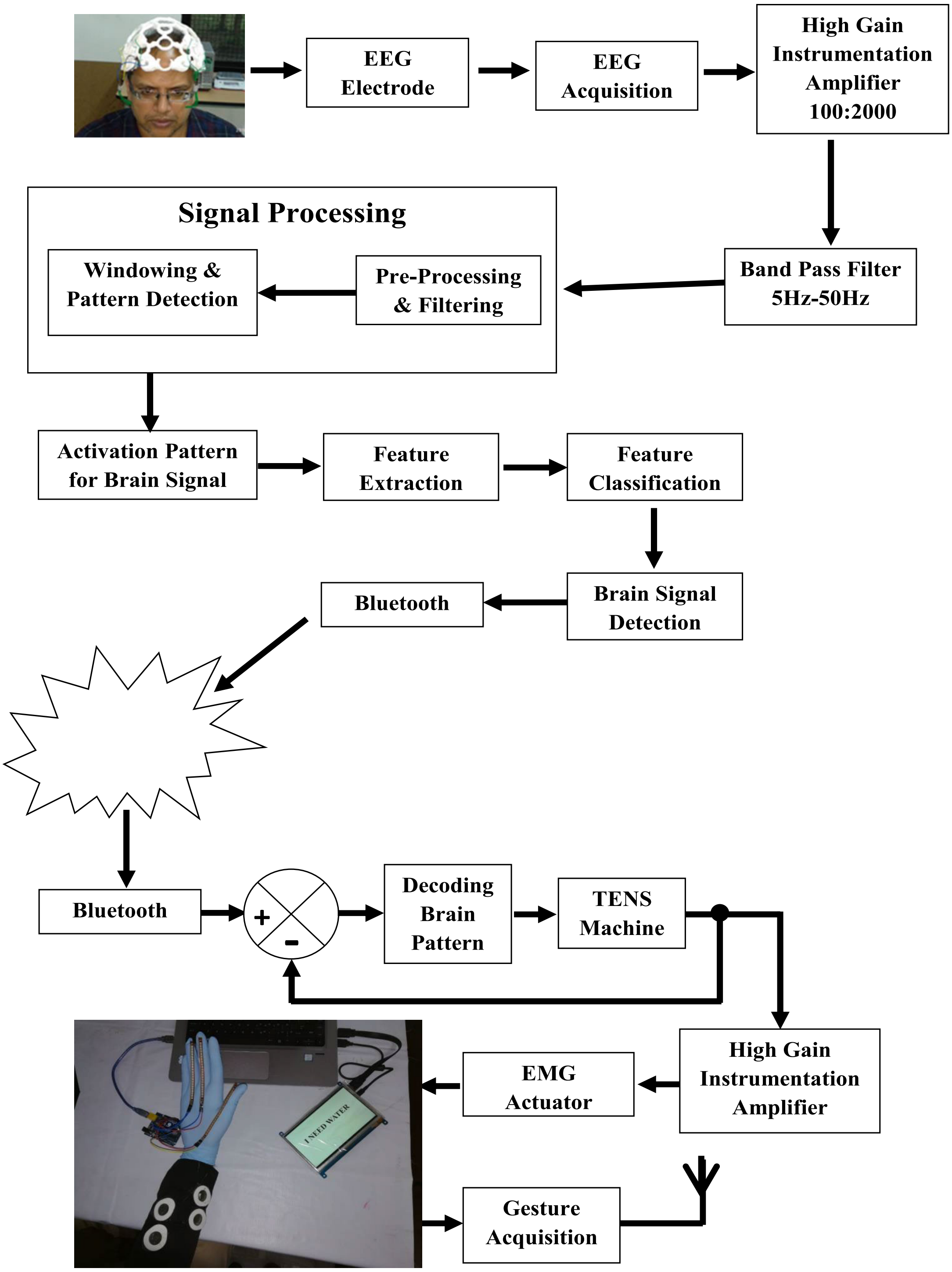

FIGURE 1. System architecture: AMIDL EEG acquisition and muscle stimulation modules.

Using the current value in the first integral and in the second integral we will have,

$$I_{H-P-R-R} = I_{H-P-G-Ru}\left(V_{H-P-G}, V_{H-P-G-Ru}\right) + I_{H-P-Ru-R}\left(V_{H-P-Ru}, V_{H-P-R}\right) \quad (6)$$

The mathematical model of the system can be summarized as I_{H-P}, as shown at bottom of the next page.

IV. SYSTEM ARCHITECTURE

The architecture of the proposed system is presented in figure 1.

A. AMIDL EEG ACQUISITION MODULE

The system architecture is designed using modular approach, it consists of three main modules. They are 1) EEG Acquisition Module, 2) Muscle Stimulation Module and

3) Gesture to Voice Conversion Module. Figure 1 indicates the two main modules of the system. The system captures brain signal using EEG sensor module, which has 14 electrodes to make measurement and two acts as reference. The acquired signal undergoes pre-processing, feature extraction and classification. The low amplitude EEG signal is amplified using high gain instrumentation amplifier with a gain of approximately 1000-2000 db. The signal is band limited by employing band pass filter having a pass band frequency of 5-50Hz.Windowing and pattern selection is utilized for getting finite response. Feature coefficients of the signal are extracted using Walsh Hadamard Transform (WHT). These extracted features are used to classify the thoughts into six different movements. The actual brain pattern is reconstructed using the transmitter Hadamard coefficients. The decoded brain pattern is given to the TENS device, which transforms the thought into muscular actions. The muscle inspired algorithm stored in the controller facilitates the process of conversion. In the offline phase, muscle movements correspond to the six different pre-defined hand postures are recorded to create the database. The hand postures are recorded using 7 Electromyography (EMG) sensors on the different hand muscles. Five EMG electrodes are placed on the finger muscles to record finger activity. Two electrodes are placed on either side of the elbow to identify roll movements. In the online phase, brain signal based on the human thought is acquired and transformed into muscle movement. This transformed muscle movement is then correlated with the recorded muscle movements. The signal with superior characteristics is selected by the controller for producing movements on the affected body part. If the brain signal fails to provide sufficient activation, periodic movements in the upper limb will be triggered by artificial muscle.

B. AMIDL GESTURE TO VOICE CONVERSION MODULE

If the brain signal with superior features activate the upper limb, the created gesture will be captured. Flex sensors placed on each finger is used for acquiring the gesture. The captured gesture will be recognized by the algorithm and transforms it into voice commands for the care givers. Figure 2 depicts the AMIDL gesture to voice conversion module. This module is used to give emergency alert messages to the caregivers or relatives.

The main hardware designed for the system has two parts 1) Acquisition module and 2) Muscle stimulation module. The brain signals of the user are acquired by using the EEG sensor. The non-invasive EEG sensor employed captures human intentions using 16 electrodes placed in the structure.14 electrodes are used for capturing the signal and two electrodes act as reference. Figure 3 depicts the capturing of EEG signal using sensor from a human subject. The acquired signal is amplified using high gain instrumentation amplifier. The signal is band limited by employing band pass filter with pass band frequency in range of 5-50Hz

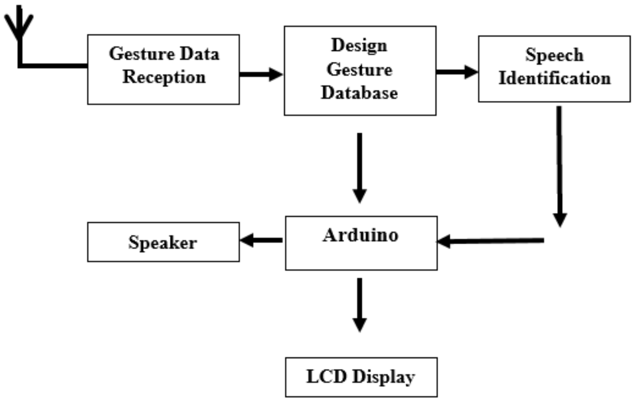

FIGURE 2. AMIDL gesture to voice conversion.

FIGURE 3. Signal acquisition using EEG sensor [21].

Signal undergoes further pre-processing and filtering to reduce the high frequency noise. Frequency domain conversion of the signal is done by using WHT transform and finite sample is selected using window technique. The design uses microcontroller in the acquisition and muscle stimulation module. The microcontrollers communicate with each other using Bluetooth technology. Bluetooth is selected because of short distance between modules and data rate required is less than 1mbps. EEG sensor and other electronic circuits are interfaced to the microcontroller to design the PCB. Figure 4 shows the electronic assembly used in our experimentation.

The muscle stimulation module receives the data using wireless module. The received data is converted into muscle movements or stimulation using muscle inspired algorithm stored in Arduino along with the TENS device interfaced to it. The output of the TENS is connected to the EMG electrode through EMG shield to activate the affected upper

$$I_{H-P} = \begin{Bmatrix} I_{H-P-R}\left(V_{H-P-G}, V_{H-P-R}\right) & for\ V_{H-P-G} < V_{H-P-T} \leq V_{H-P-R} \\ I_{H-P-G-Ru}\left(V_{H-P-G}, V_{H-P-Ru}\right) & for\ V_{H-P-G} < V_{H-P-T} \leq V_{H-P-Ru} \\ I_{H-P-Ru-R}\left(V_{H-P-Ru}, V_{H-P-R}\right) & for\ V_{H-P-Ru} < V_{H-P-T} \leq V_{H-P-R} \end{Bmatrix}$$

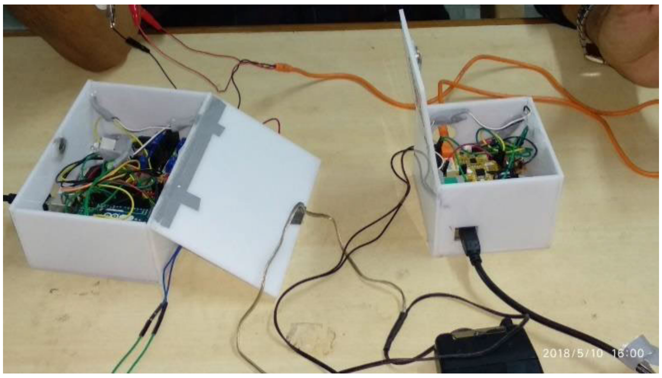

FIGURE 4. PCB designed for the experimentation.

FIGURE 5. Acquisition and stimulation process.

limb movements. The EMG shield helps to customize the stimuli produced by the TENS device. The entire assembly used for acquisition and stimulation is depicted in figure 5.

V. RESULTS AND DISCUSSION

Experimentation is carried out in two phases, offline training phase and online recognition phase. Experimentation and validation are done on 10 healthy and 10 paralyzed subjects. In offline phase EEG activity of the paralyzed and EMG activity of the healthy subjects were recorded. In the training phase, subjects were given the familiarization of six different intended actions like, Grasp, Release, Rollup, Rolldown, Rollup Release etc. Multimedia feedback is given to the subjects to enhance the brain patterns. The subjects are enlightened by using encourages messages and appreciation speeches in the feedback, rather than simple live streaming the actions. Rollup-grasp, Rolldown-Release movements of the upper limb are used for communicating the need to the caregivers. In the online phase, user thoughts are recognized and converted into muscular action. The generated muscular action is correlated with the EMG activity of the healthy subjects. Based on the correlation result microcontroller selects the superior signal, which is used for stimulating the affected body part.

A. RESULTS COMPARISON OF EEG ACTIVATED AND POSTURE ACTUATED MOVEMENTS

Figure 6 shows the correlation of brain actuated real time EMG and posture actuated EMG for the subject intention to

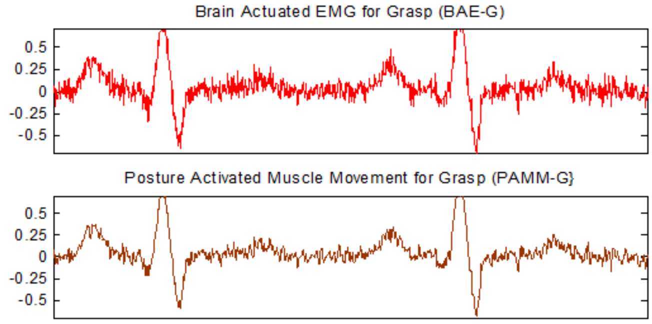

FIGURE 6. EMG activity for attempting grasp movements.

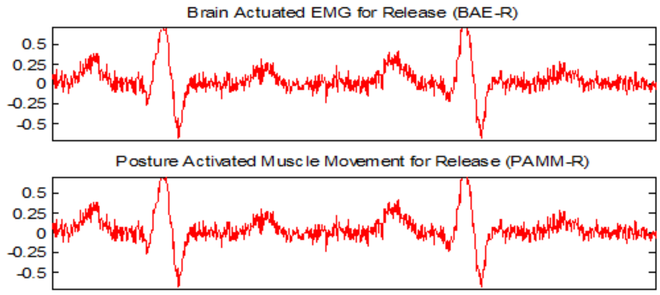

FIGURE 7. EMG variations corresponding to release movement.

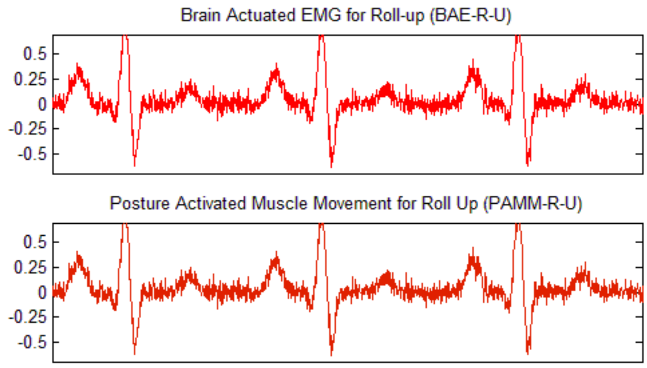

FIGURE 8. EMG activity based on ROLL up upper limb movement.

grasp the object. The EMG activity is recorded using EMG electrodes and measurement is done using Digital Storage Oscilloscope (DSO). The graph shows the amplitude variations of EMG signal with respect to frequency. The amplitude is normalized between $+/-$ 0.5mv and frequency range used is 0-500Hz.

Figure 7 indicates the EMG variations observed in brain actuated and posture activated movements corresponding to human intention of "Release". Based on the correlation result brain actuated signal is selected for the stimulation of upper limb. Figure 8 shows the real time and recorded EMG activity for "Roll up" movement. Roll up movement is recorded using two electrodes placed on the either side of the Elbow. The rollup movement requires high intensity stimulation. In most of the time brain actuated EMG fallen below the desired level, so the stimulation of affected part is initiated in this case by artificial muscle movements. Figure 9 shows the EMG actuated by real time human Intention and the EMG activity produced using the training of "roll down" hand

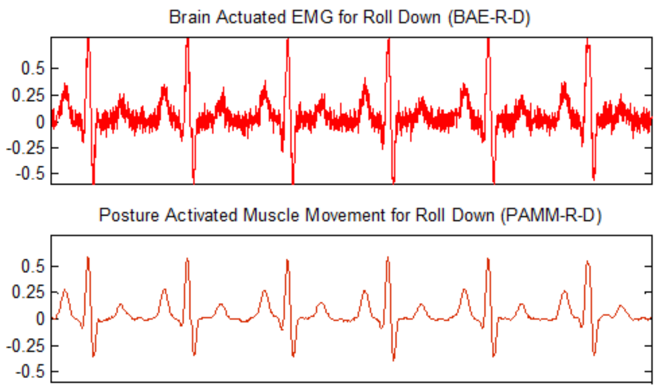

FIGURE 9. EMG activity based on ROLL down upper limb movement.

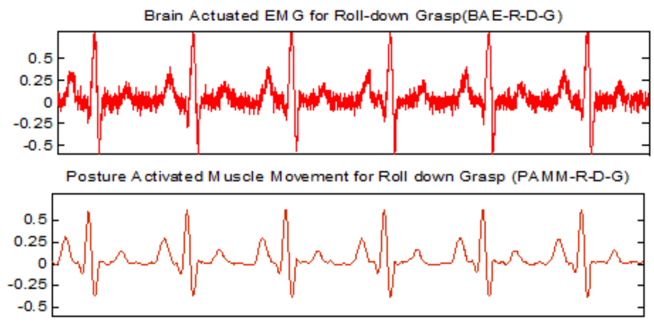

FIGURE 10. EMG activity for the gesture roll down-grasp.

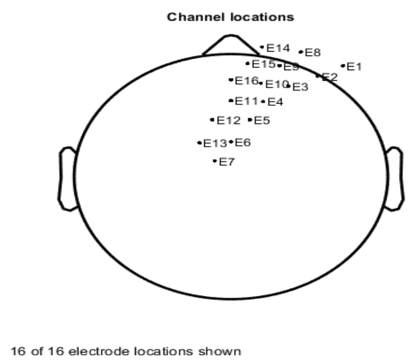

FIGURE 11. Electrode placement on the brain [21].

Posture. Roll down ideally requires low intensity signals, so in this movement selection priority is given to signal with low signal strength in the correlation. Figure 10 shows the EMG data acquired for the gesture "Roll down-grasp". This EMG activity is used for communicating the paralyzed subject's need to the caregivers.

B. RESULT OF EEG PATTERNS ON THE REALISTIC HEAD MODELS

Realistic head models are used for the analysis of EEG signals. EEG sensors with 16 electrodes are used for the capturing the brain signals. The unique electrode placement scheme used in this experimentation is shown in figure 11. The placement scheme mainly concentrated on the frontal and parietal regions of the brain.

The variations of brain patterns with different frequencies are analyzed to facilitate the feature extraction and classification process.

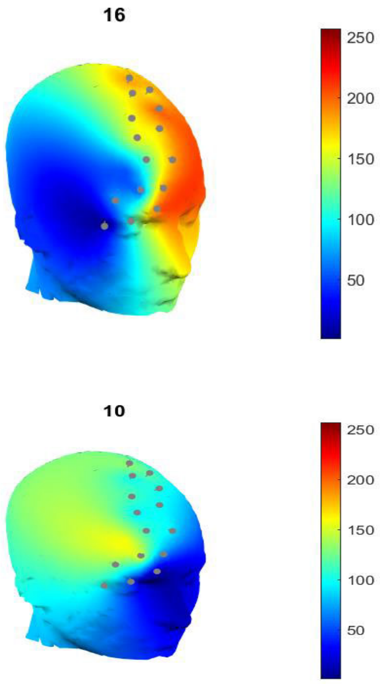

FIGURE 12. Brain pattern comparisons with and without multimedia feedback [21].

TABLE 2. Data statistics for brain actuated Rollup signal.

STATISTICAL PARAMETERS	X COEFFICIENT VALUES	Y COEFFICIENT VALUES
Min	1	0
Max	64	9
Mean	32.5	4.734
Median	32.5	5

In figure 12 red indicated the maximum interaction of neuron and blue indicates minimum interaction of neurons. The neuron connectivity in the head model on the left is improved when multimedia feedback is used, compared to the figure on right which does not use feedback.

C. STATISTICAL ANALYSIS OF GENERATED EMG SIGNAL

Statistical analysis is carried out to determine the correlation between Brain actuated EMG signal and posture actuated EMG signal. The data obtained during Rollup and Rolldown movement of the upper limb are utilized for the analysis.

Correlation matrix help to identify whether the human intentions match the recorded muscle movements. This matrix acts as a second level of classifier before the final actuation of the body part is made.

Correlation Matrix obtained

[1.0000 0.0867 0.0867 1.0000]

Correlation matrix obtained

[1.0000 −0.0640 −0.0640 1.0000]

Correlation matrix help to identify whether the human intentions match the recorded muscle movements.

TABLE 3. Data statistics for posture actuated Rollup signal.

Statistical parameters	X coefficient values	Y coefficient values
Min	1	-9.392
Max	64	8.982
Mean	32.5	-0.1296
Median	32.5	-0.09542
Mode	1	-9.392
Standard deviation	18.52	5.665

TABLE 4. Data statistics for brain actuated Rolldown signal.

Statistical parameters	X coefficient values	Y coefficient values
Min	1	0
Max	64	9
Mean	32.5	4.719
Median	32.5	4.5
Mode	1	0
Standard deviation	18.52	3.16

TABLE 5. Data statistics for posture actuated Rollup signal.

Statistical parameters	X coefficient values	Y coefficient values
Min	1	-9.392
Max	64	8.982
Mean	32.5	-0.1496
Median	32.5	-0.07542
Mode	1	-7.392
Standard deviation	18.52	4.665

This matrix acts as a second level of classifier before the final actuation of the body part is made.

D. RESULTS OF CLASSIFICATION ACCURACY OF DIFFERENT SUBJECTS

The classification accuracy of the system is verified by performing the test on 10 healthy subjects and 10 paralyzed persons. Maximum obtained 88% efficiency and on an average 80.45% classification accuracy based on the six different human intentions for upper limb movements. The experimentation result shown in figure 13 is the summary of results on 20 participants. U1-U10 are represent healthy subjects, U11-U20 represents paralyzed persons. The reason for improved accuracy for classification among subjects is

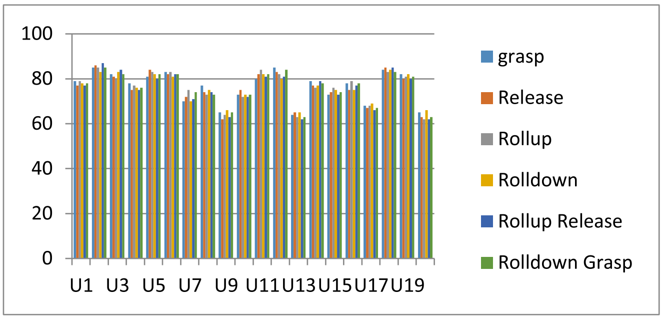

FIGURE 13. Classification accuracy of six different movements on 20 subjects.

due to systematic training undertaken and usage of feedback. The healthy subject U2 is an experienced user and is more familiar with similar interfaces, obtained high accuracy. However, the unhealthy subjects U11 and U12 also obtained high accuracy through their dedication and passion. Visual feedback and voice encouragement are also given to paralyzed during training. The participants U9 and U13 has shown similar low classification accuracy due to their age and unfamiliarity with the system

The authors used EEG signal to identify the human Intentions and to control upper limb movements of the paralyzed person. Artificial muscle movements are integrated into the system to get continuous movement of the affected body part. Recorded muscle movements help to enhance the rehabilitation process. The burden of carrying exoskeleton is avoided by incorporating by using innovative assembly. The communication aid for the paralyzed is provided by implementing gesture recognition module. AMIDL obtained better classification accuracy compared to many existing methods mentioned in the literature. The two-level classification employed in the system help to reduce false operations. The future research should focus on reducing human workload by incorporating efficient controllers. Accuracy of mapping human intentions with muscle movements has to be increased. Machine leaning algorithms that can effectively map human intentions to the desired muscle movements are the way forward.

VI. CONCLUSION

AMIDL system with 3 different modular units is designed and implemented. The system validation is carried out by performing online and offline testing on 10 healthy and 10 paralyzed subjects. AMIDL is designed to perform six different movements like Grasp, Release, Rollup, Rolldown, Rollup Release, Rolldown Grasp on the paralyzed upper limb. WHT transform is utilized for feature extraction and classification of EEG signals. The EMG activity of the healthy subjects are correlated with the real-time EMG signals generated by the paralyzed. Selection criteria for the ideal signal is finalized based on the EMG analysis carried out on all six hand postures. The two-level classification method improved the accuracy of the system. The system produced continuous response even in the presence of uncertain real-time inputs.

Results indicate that mental fatigue and miss-operations are reduced. The burden of carrying exoskeleton is minimized by an innovative assembly having array of sensors and control units. Periodic stimulation in the absence of ideal brain signal enhance the rehabilitation process. Gesture Recognition method is utilized for providing communication aid for the paralyzed. In our future work, we are trying to incorporate closed loop controller with haptic feedback. Deep learning algorithms will be used to effectively map EEG signals with recorded EMG signals. The user experience can be enhanced by measuring the user emotions while performing the different activities.

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