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Brain-Controlled Adaptive Lower Limb Exoskeleton for Rehabilitation of Post-Stroke Paralyzed

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ABSTRACT Stroke is a standout amongst the most imperative reasons of incapacity on the planet. Due to partial or full paralysis, the majority of patients are compelled to rely upon parental figures and caregivers in residual life. With post-stroke rehabilitation, different types of assistive technologies have been proposed to offer developments to the influenced body parts of the incapacitated. In a large portion of these devices, the clients neither have control over the tasks nor can get feedback concerning the status of the exoskeleton. Additionally, there is no arrangement to detect user movements or accidental fall. The proposed framework tackles these issues utilizing a brain-controlled lower limb exoskeleton (BCLLE) in which the exoskeleton movements are controlled based on user intentions. An adaptive mechanism based on sensory feedback is integrated to reduce the system false rate. The BCLLE uses a flexible design which can be customized according to the degree of disability. The exoskeleton is modeled according to the human body anatomy, which makes it a perfect fit for the affected body part. The BCLLE system also automatically identifies the status of the paralyzed person and transmits information securely using Novel-T Symmetric Encryption Algorithm (NTSA) to caregivers in case of emergencies. The exoskeleton is fitted with motors which are controlled by the brain waves of the user with an electroencephalogram (EEG) headset. The EEG headset captures the human intentions based on the signals acquired from the brain. The brain-computer interface converts these signals into digital data and is interfaced with the motors via a microcontroller. The microcontroller controls the high torque motors connected to the exoskeleton's joints based on user intentions. Classification accuracy of more than 80% is obtained with our proposed method which is much higher compared with all existing solutions.

INDEX TERMS Artificial skin, assistive technologies, brain-computer interface (BCI), electroencephalogram (EEG), brain-controlled exoskeleton, paralyzed, stroke.

I. INTRODUCTION

Stroke is an important reason of physical disability in developed countries, and in fact the third most common reason [1]. Almost 80% of survivors of stroke have experienced movement impairment on one side of the body [2-3]. Hand or arm impairment is particularly disabling and persistent, and lead to reduced quality of life [3-4]. Many of the stroke survivors have a less physical disability by the end of the first three months (almost in all cases). Nearly, 35% of survivors having an initial paralysis of the leg do not regain the basic and essential function, and 20 to 25% of all the survivors are not able to walk without complete physical assistance [5]. Within six months, nearly 65% of patients are unable to use the affected hands for doing common life activities. Most of the patients are thus forced to be dependent on others in the remaining part of life.

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Exoskeleton has emerged as one of the major solutions for the above-said problem. The exoskeleton can be used for providing rehabilitation training and also for walking assistance to patients affected by post-stroke disability. The traditional methods used for controlling the movement of exoskeleton are accelerometers, potentiometers and different types of sensors. In recent years' researchers are focused on EEG signals as the method for controlling the robotic action. Wheelchairs and robotic arms are controlled by using human brain signals [6]. The quality of life among people with physical disability can be improved by interacting with BCI controlled robot [7]. Home auxiliary robot platform based on BCI facilitates people with disability to perform practical activities [8]. The shared control is implemented through mobile robot for the user to interact with remote environments [9]. Human locomotion and gait rehabilitation are also implemented using BCI controlled robots [10]. Lee et al. realized BCI controllers based on EEG signals for wearable devices [11]. Few exoskeletons based solutions have also been proposed for Paraplegia or lower limb paralysis which is a spinal cord injury that paralyzes the lower limbs [12]. This BCI based exoskeleton was designed by decoding the signal of EEG related to the user. Some movements like sitting, walking forward, standing, etc. were realized and to activate the brain, SSVEP (Steady State Visually Evoked Potential) was used [13]. A visual stimulation based on SSVEP at a certain frequency provides the advantages of high bandwidth and short training time [14]. Motor Imagery (MI) task-based BCI systems are designed, in which user performs MI of limb that is encoded into the EEG readings. The features representing particular duty are decoded and also transferred to commands for controlling the assistive robots [15]. CCA (abbreviated for canonical correlation analysis) is used to recognize frequency component of SSVEP in EEG signals [16]. Recognition accuracy is higher than that of traditional methods like FFT (Fast Fourier Transform), used for spectrum estimation. Distinct patterns extracted from EEG with autonomous selection are realized using filter bank common spatial pattern (FBCSP) [17]. FBCSP with a specific combination of feature selection and classification algorithm produces higher validation accuracies.

Current alternatives for this project in the market is a BCI controlled wheelchair and electric wheelchair. This does not allow for the overall movement of the paralyzed body, and is only a mode of transportation for the paralyzed person. Since the paralyzed body is motionless, it stiffens the muscle tissues causing discomfort. Various other exoskeletons that are controlled using BCI uses mental commands to control every movement. This is slower and inaccurate. It also provides a huge load on the system and makes the whole system slower [17-18]. In our previous work we have created an alternative to exoskeleton, in which the affected body part is stimulated using a noninvasive model called the Muscle to Machine Interface for Paralyzed person (MMIP). Muscle nerves are exited using muscle electrodes based on the movements produced by the care giver [19]. We further extended this work to activate the muscle nerves using paralyzed person's thoughts [20]. The brain to brain secure communication is achieved using Novel-T symmetric encryption algorithm (NTSA) [21].

In our proposed work, we use gyroscope in the BCI headset to control the directions along with only two mental commands. This reduces the load on the system and increases the speed of the exoskeleton. The exoskeleton interfaced with the brain is controlled based on the decoded brain signals. In correspondence to the mental commands recognized, the high torque motors connected to the joints of the exoskeleton are activated. The exoskeleton is made using carbon fiber which makes it light and hence user-friendly. The exoskeleton replicates the movement of a healthy functioning leg using all the joints. Sensory feedback is introduced to reduce the system false rate. The user intentions given to the system are converted to motor actions. If the produced motor action is not sufficient to trigger the actual limb movement, an adaptive algorithm is used to make the corrective action. The status of the paralyzed and emergency rescue information is transmitted wirelessly to the corresponding caregivers. NTSA encryption and decryption algorithm is used to transmit the information securely to the intended user without interference. Walsh–Hadamard transform is used for feature extraction of brain signals. The extracted features along with Hadamard coefficients are transmitted wirelessly from brain to the lower limb via Bluetooth. At the receiver side using the Hadamard coefficients, the original brain signals are reconstructed. The feature extraction and reconstruction is implemented for all five different user intentions. The Brain-Controlled Lower-Limb Exoskeleton (BCLLE) analyses the human thoughts and transforms it into different movements on a unique lower limb structure.

The contributions of our research are,

- A Brain-Controlled Lower-Limb Exoskeleton (BCLLE) in which the exoskeleton movements are controlled based on user intentions.
- An adaptive mechanism based on sensory feedback integrated with the exoskeleton to reduce the system false rate.
- A flexible design for the exoskeleton which can be customized according to the degree of disability.
- Artificial skin incorporated with sensors which can provide a sense of touch to the body parts of users.
- Automatic identification of the status of the paralyzed person and secure transmission of information to caregivers in case of emergencies

The rest of this paper is structured into five sections on which section II explains the different existing exoskeleton models controlled by BCI. In section III the System Architecture is explained with details of the 3-D models of the exoskeleton. Section IV depicts the design of different modules of BCLLE system and explains the application of Walsh–Hadamard transform. Implementation and experimental results are given in the last section (section V). Finally, section VI is conclusion of our work and presents some future research directions.

II. RELATED WORKS

In this section we discuss few existing exoskeleton solutions with Brain-Computer Interface proposed foe paralyzed people. But the problem with most of them is that the users neither have control over the tasks nor can get feedback with respect to the status of the exoskeleton. Additionally, there is no arrangement to detect the user movements or accidental fall. Our research focuses exoskeleton on overcoming this major problem and provides an efficient and flexible solution.

Rehabilitation Training is provided to people with disabilities using a hybrid exoskeleton controlled by BCI, based on motor imagery tasks [23]. The grasping and release of ball using BCI controlled exoskeleton were demonstrated on people suffering from motor neuron diseases [24]. A closed-loop BMI system to control an ambulatory exoskeleton-without any weight or balance support-for gait rehabilitation of incomplete spinal cord injury (SCI) patients was presented in [25]. An adaptive BMI paradigm that works with decoding cognitive brain signals was introduced in [26]. Wang *et al.* conducted preliminary research on brain-controlled prostheses for people with spinal code injury [27]. NeuroRex [28], an EEG based Brain-Machine Interface for lower body robotic exoskeleton is used to assist people who cannot walk independently. Strategies for motor imagery task detection from EEG are discussed [29]. Adaptive strategies were able to achieve good accuracy comparable with subject-specific models. BCI-Manus therapy is used for effective rehabilitation of upper limb [30]. Revised brain symmetry (rBSI) is correlated with motor imagery tasks and used as a measure of stroke rehabilitation. Gait phase identification is done using only joint angular sensor [31]. This method helped to simplify the sensor system of lower limb exoskeleton. Numerous research has also focused on efficient solutions and applications based on Internet of Things [32-33] and fog computing [34-35] reviewed the current state of research of EEG based control for upper and lower limb exoskeleton. Virtual reality environment for spinal cord injury (SCI) patients based on BCI to achieve specific goals were designed [36]. The online control of Rex exoskeleton using EEG signal from the subject's sensorimotor cortical networks was demonstrated [37]. Lokmat Pro exoskeleton was employed as walking assistant based on user's intentions, and also incorporated body weight system (BWS) with assisted rehabilitation [38]. Liu et al. proposed Gait training using brain-controlled exoskeleton with 3 degrees of freedom [39]. EEG signals recorded from motor cortex are used to control the robot through TCP/IP protocol. Xu *et al.* devised a system that was intended for stroke rehabilitation and uses BCI driven motorized ankle-foot orthoses (BCI-MAFO). The detection of imaginary dorsiflexion movements could be done using the system within a short latency by the analysis of MRCPs. Whenever the dorsiflexion movements are detected, the MAFO was triggered to elicit passive dorsiflexion, thereby providing binary control of robotic orthosis to the user [40]. A BCI controlled robotic quadcopter using noninvasive scalp electroencephalogram (EEG) in human subjects was discussed in [41]. An analysis of upper limb movements in the time-domain of low-frequency electroencephalography (EEG) signals was carried out in [42]. Brain signals are analyzed using band power and radial basis function and implemented on the wheel chair [43]. A non-contact control system is designed that allows the paralyzed patients to get assistance in the hospital by activating the nurse emergency system and adjusting other appliances. The patients can wear EEG acquisition device with electrodes for monitoring patient EEG signal to convert into relevant commands for adjusting the devices [44]. An adaptive neuro-fuzzy classifier is devised to identify and monitor the EEG based BCI for motor imagery (MI) task. In order to enhance the accuracy of the classification technique, an optimization algorithm is integrated with neuro-fuzzy inference systems [45]. A unique biometric signature for an individual is generated by the combination of hand kinematic synergies and their neural representations. Lin et al. proposed upper limb rehabilitation system merging motion tracking device, EEG device and virtual reality game. The training system developed enhanced motor functions and assistance in rehabilitation [46]. BCI Speller utilizing eyes-closed (EC) and double-blinking (DB) EEG signals and a three-class support vector machine will be developed. The system used EC as "select command" and a DB as "undo" command, demonstrated good accuracy and spelling rate [47]. The effect of acute stress on brain activity is evaluated utilizing task switching. The executive functions were enhanced under stressful condition with improved performance in task switching [48].

In most of the proposed methods, the users neither have control on the operations nor can get feedback regarding the status of the exoskeleton. Moreover, there is no provision to detect the user movements or accidental fall. In this research work, the proposed system solves these issues using a Brain-Controlled Lower-Limb Exoskeleton (BCLLE) in which the exoskeleton movements will be controlled based on user intentions. An adaptive mechanism based on sensory feedback is integrated to reduce the system false rate. BCLLE uses a flexible design which can be customized according to the degree of the disability. The exoskeleton also is modeled according to human body anatomy, which makes it a perfect fit for the affected body part. The sense of touch is provided to the body parts by incorporating the artificial skin integrated with sensors. The system can also accommodate wide range of age groups with fewer modifications. The BCLLE system also automatically identifies the status of the paralyzed person and transmits information securely using NTSA to the caregivers in case of emergencies. The exoskeleton is fitted with motors which are controlled by the user's brain waves using an Electroencephalogram (EEG) headset. EEG headset captures the human intentions based on the signals acquired from the brain. Brain-Computer Interface converts these signals into digital data and is interfaced to the motors via a microcontroller. The microcontroller controls the high torque motors connected to the joints of the exoskeleton based on the user intentions.

III. MATHEMATICAL MODEL

In this section we present the mathematical analysis of the proposed system. The joint variable μ_r having multiple line m_l is defined. The expected motion joint at the junction is defined as $l_r(t)$.

Using the PD control with feed-forward we have the voltage $V_\mu(t)$ acting at joints,

$$V_\mu(t) = \frac{d^2}{dt^2}l_r(t) + k_v\frac{d}{dt}E(t) + k_pE(t) \tag{1}$$

where

$$E(t) = l_r(t) - l(t) \tag{2}$$

If the torque "$T_\mu(t)$" is taken instead of voltage $V_\mu(t)$, the control law becomes

$$T_\mu(t) = \frac{d^2}{dt^2}l_r(t) + k_v\frac{d}{dt}E(t) + k_pE(t) \tag{3}$$

The control of motor and the exoskeleton joints are independently managed. The physical quantities $l_r(t)\, andl(t), T_\mu$ are vector of (m × 1) and k_p and k_l are (m × m) gain matrix for proportional derivative controller which is positive.

The lower body exoskeleton is governed by dynamic equations at motion,

$$T_\mu(t) = [M_p(l)]\frac{d^2}{dt^2}l + C_{cc}\left(l, \frac{dl}{dt}\right) + g_v(l) + f\left(l, \frac{dl}{dt}\right) \tag{4}$$

where $M_p(l)$ is m × m matrix of mass manipulation, $C_{cc}(l)$ is (n × 1) matrix for centripetal manipulation, $g_v(l)$ is (n × 1) matrix for gravity manipulation and $f(l)$ is (n × 1 matrix for friction manipulation.

$$T_\mu(t) = \gamma T_\mu(t)' + \theta \tag{5}$$

where $\gamma = M_p(l)$ and $\theta = C_{cc}\left(l, \frac{dl}{dt}\right) + g_v(l) + f\left(l, \frac{dl}{dt}\right)$ and from the equation at motion $T_\mu(t)' = \frac{d^2l}{dt^2}$

It is basically a unit inertia operation with input as $T_\mu(t)'$. The θ and γ are the dynamic parameters used. This proves the cancellation of all coupling and non-linearity and the process changes to linear-decoupled system.

Choosing $T_\mu(t)' = T_\mu(t)$ the error evaluation will be formed as,

$$\frac{d^2}{dt^2}E(t) + k_v\frac{d}{dt}E(t) + k_pE(t) = 0 \tag{6}$$

This signals that the expected performance is not always possible. The time required to calculate γ and θ, $T_\mu(t)$ changes in that span of time. The parameter such as centripetal, inertia and mass are unknown. Let the variation of this parameter at time 't' is given by,

$$M_p(l)^*, C_{cc}\left(l, \frac{dl}{dt}\right)^* g_v(l)^* \text{ and } f\left(l, \frac{dl}{dt}\right)^*$$

Then the error equation is given by,

$$\begin{aligned}&\frac{d^2}{dt^2}E(t) + [k_v]\frac{d}{dt}E(t) + k_pE(t)\\ &= M_p(l)^{*-1}\left[M_p(l) - M_p(l)^*\right]\frac{d^2}{dt^2}l(t)\\ &\quad + (C_{cc}(l) - C_{cc}(l)^*) + (g_v(l) - g_v(l)^*) + (f(l) - f(l)^*)\end{aligned} \tag{7}$$

If both $M_p(l)\, andM_p(l)^*$ are same then exactly cancel each other. The control law states that

$$V_\mu(t) = k_{pl}(\gamma_{ld} - \gamma_l) - k_{vl}\frac{d}{dt}\gamma_l \tag{8}$$

The voltage r_μ is applied to motor for different values of 'l'

$$\hat{V}_{\mu d} = \gamma_{ld} + \frac{1}{k_{pl}}\frac{d^2}{dt}\gamma_{ld} + \frac{k_{\gamma l}}{k_{pl}}\frac{d}{dt}ld \tag{9}$$

$$V_l(t) = k_{pl}(\gamma_{ld} - \gamma_l) - k_{\gamma l}\frac{d^2}{dt^2}\gamma_l \tag{10}$$

$$V_l(t) = \frac{d^2}{dt^2}\gamma_{ld} + k_{pl}(\gamma_{ld} - \gamma_l) + k_{\gamma l}\left(\frac{d}{dt}\gamma_{ld} - \gamma_l\right) \tag{11}$$

$$\hat{V}_{ld} = \frac{\gamma_{lmd}}{k_{pl}} + \gamma_{ld} + \frac{1}{k_{pl}}\frac{d^2}{dt^2}\gamma_{ld} + \frac{k\gamma_l}{k_{pl}}\frac{d}{dt}\gamma_{ld} \tag{12}$$

where γ_{lmd} corresponds to T_{lmd}

IV. SYSTEM ARCHITECTURE

The system design comprises of an exoskeleton that replicates a lower limb, which is made using carbon fiber. The exoskeleton has total six degrees of freedom including both legs, one on each side of the pelvic bone, one on each knee and one on each ankle. Thus three degrees of freedom on each leg making it total of six degrees of freedom on the entire exoskeleton. Each joint of the lower limb are actuated using high torque motors. The movement of the exoskeleton is facilitated by controlling the degree of rotation of the motors. This exoskeleton is strapped onto the abdomen as well as foot region for improving the stability and balance of the person. Support is also provided on the back side of the ankle region. The angle sensors are placed on the joints to provide feedback regarding the status of exoskeleton. This sensor is also used to validate whether the applied force is sufficient to stabilize the exoskeleton.

The fall detection mechanism is implemented by placing an accelerometer on the back side of the lower limb to measure the tilt. If the measured sensor value crosses the threshold, a message will be given to the care givers for emergency rescue. Figure 1 depicts the proposed system architecture.

The exoskeleton is controlled through human intentions. Electroencephalograph (EEG) sensor uses non-invasive method to collect the brain signals from the scalp of the person. EEG sensor has 16 electrodes incorporated in structure, where two electrodes act as the reference for measurement. The conductivity of the electrodes is improved by using gold plating. The signals collected are amplified using high gain

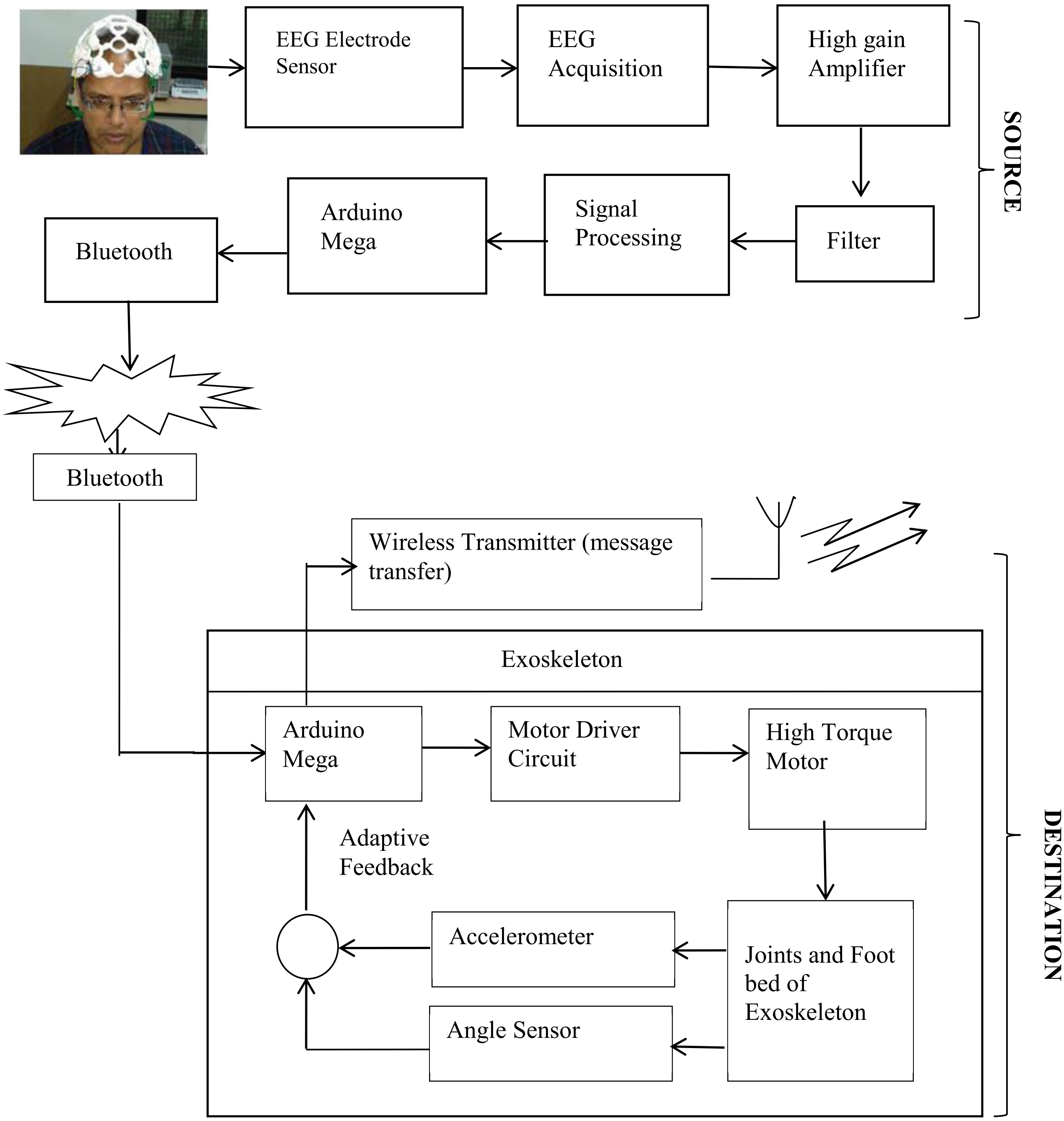


FIGURE 1. System architecture of brain actuated multidimensional exoskeleton.

amplifier and a band pass filter is used for filtering high-frequency noise. In the signal processing stage, the signal undergoes further preprocessing and filtering. The suitable pattern based on the mental command is selected by using windowing technique. The signal is converted into digital data which is given as input to the microcontroller. The microcontroller does the classification of each mental command based on the feature extraction. In the training phase, user will be trained for five basic commands (sitting, standing, forward movement, right turn, left turn). The recorded patterns during the training phase will be used by the microcontroller for decision making. The recognized thought patterns will be mapped to five different commands. During the testing phase, the controller makes use of machine learning to recognize and match patterns in the input data along with the training data that is already stored in the system to make the necessary decision regarding the action to be performed. The activation command to the exoskeleton is given by the controller through Bluetooth module. At the receiver side the microcontroller converts this command into motor action

FIGURE 2. Emotive EPOC mobile EEG headset.

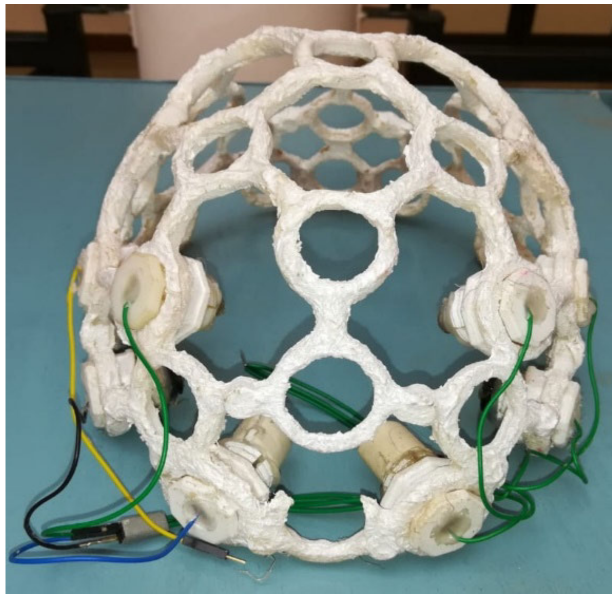


FIGURE 3. EEG Sensor with electrodes.

which in turn moves the desired parts of the exoskeleton. Using a three-level sensing mechanism, feedback is given to the microcontroller regarding the status of the exoskeleton. Based on this feedback the microcontroller makes the desired corrections on the activation signals. The sensory feedback gives more stability to the system, and moreover rescue messaging system is also implemented in case of emergencies.

The secured communication between the paralyzed person and caregiver is achieved using Novel-T symmetric algorithm (NTSA). This algorithm ensures that the data is securely transmitted to the intended caregiver. NTSA is a symmetric algorithm that uses a single 128-bit symmetric key that is agreed upon by sender and receiver for performing encryption and decryption. The 128-bit key is divided into four partial keys k0, k1, k2 and k3. There are 64 rounds with partial keys k0, k1 applied for odd rounds and k2, k3 applied for even rounds. Multiple XOR and shift operations are performed in each round of encryption. The message from the paralyzed person is encrypted using NTSA encryption algorithm to produce ciphertext.

The ciphertext is transmitted to the caregiver either through internet or wireless module. The NTSA decryption algorithm decrypts the ciphertext using the key and the original message is retrieved at the receiver-end by the care giver. The NTSA algorithm introduces key confusions in each round of encryption that makes the algorithm safe and secure from possible attacks. This algorithm uses minimum system memory and provides faster response.

In the initial stages, brain signals are monitored using Emotive EPOC mobile EEG headset. Emotive uses 14 channels to access the raw EEG data and the analysis of acquired data is carried out using integrated software tools. Figure 2 exhibits the Emotive EEG headset deployed in brain signal monitoring. In the latter stages of experimentation Emotive headset is replaced by the designed EEG Sensor. The EEG sensor is manufactured using 3D printer Technology. It has a total of 16 electrodes in which 14 are used for tapping the brain signals and two electrodes act as reference. Figure 3 shows the designed EEG sensor and its electrodes

V. SYSTEM DESIGN & METHODOLOGY

Brain-Controlled Lower-Limb Exoskeleton (BCLLE) system is an interconnection of different modular components. The design of individual modules along with their working is illustrated in this section.

A. EXOSKELETON DESIGN

The Lower limb exoskeleton is designed matching the characteristics of the human anatomy. Figure 4 depicts the complete lower body exoskeleton designed using 3D software. The important parts of the exoskeleton are labeled as below,

A → Gluteal Region
B → Hip joint
C → Thigh Region
D → Knee Joint
E → Leg Region
H → Ankle Joint
G → Foot Region

These parts are flexible and allow easy attachment and detachment. For the fully paralyzed, the complete exoskeleton will be used. In case of partial paralysis, we can detach the complete assembly into separate parts. The carbon fiber material is used for the construction of exoskeleton. This provides the exoskeleton, easier mobility and light weight. To get better adhesion to the exoskeleton two supports are designed: one over the foot region and other on the back side of the ankle joint.

Figure 5 depicts the assembly of separate parts of lower limb exoskeleton. These parts can replace the affected body parts of the paralyzed person. So people having partial paralyzes are relieved from the burden of carrying the entire

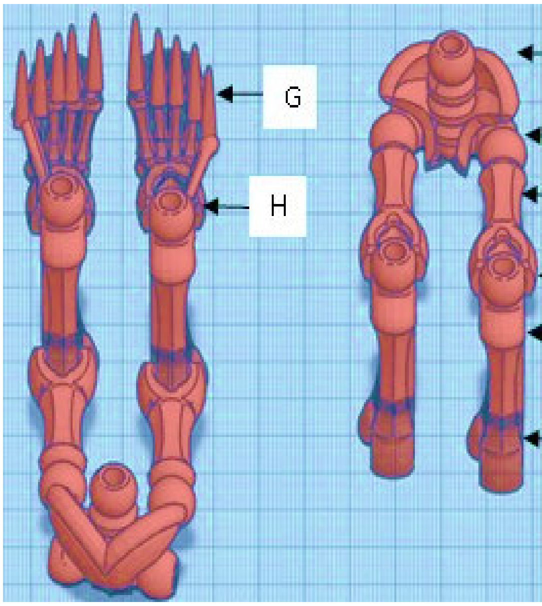


FIGURE 4. Complete Lower body part exoskeleton.

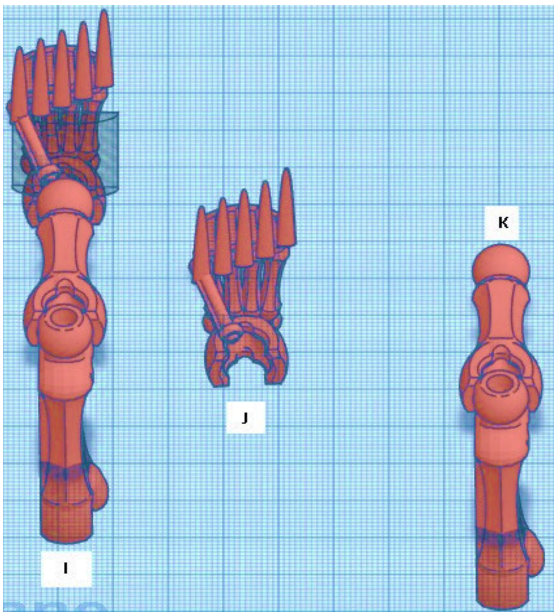


FIGURE 5. Exoskeleton of foot and its connected joint (Solid 3D Model).

assembly. The three separate parts of the lower limb labeled in the figure are as follows,

I → Complete leg region
J → Foot Region
K → Thigh and Leg region with Knee joint

Figure 6 shows the hollow 3D model of the separate parts of lower limb. High torque motors are placed at the joints of the lower limb to realize precise movement.

B. ARTIFICIAL SKIN PREPARATION

The sensor circuit is incorporated in the artificial skin to get the sense of touch or feeling for the exoskeleton. The skin will be placed over the designed exoskeleton model

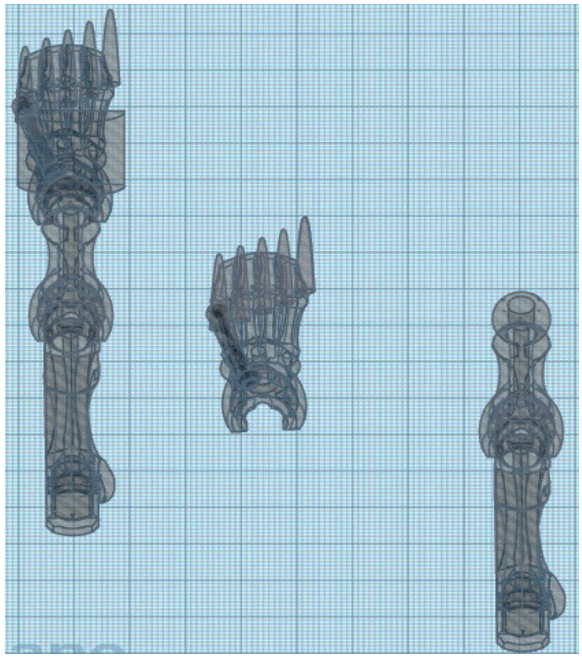


FIGURE 6. Exoskeleton of Foot and its connected joint (Hollow 3D Model).

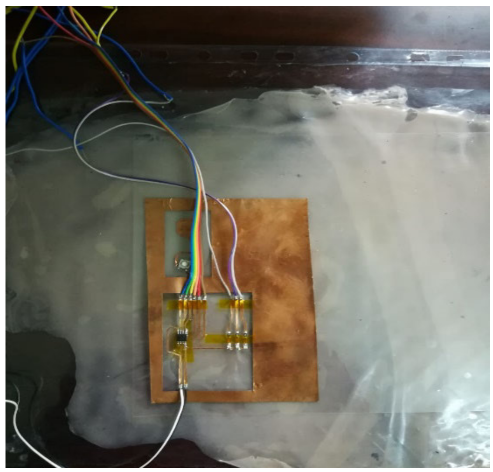


FIGURE 7. Artificial Skin along with processor and sensor circuit.

with all the essential circuits. This gives the exoskeleton the functionality and aesthetics similar to the human body parts. Silicon rubber is the material used for constructing the artificial skin. The artificial skin acts as a protective coating and binds together the entire exoskeleton structure. Figure 7 illustrates the developed artificial skin along with its SMD components. ATtiny45 microcontroller is used for capturing vibrations and sense of touch using different sensors integrated into the circuit. The PCB design of the circuit is done using Fritzing software which is an open source tool for PCB design. The design is optimized for compactness by appropriate placement of components and reducing the line width.

C. FEATURE EXTRACTION AND CLASSIFICATION

In the offline phase, training is provided to the user using visual stimulation interface. The database is designed for all

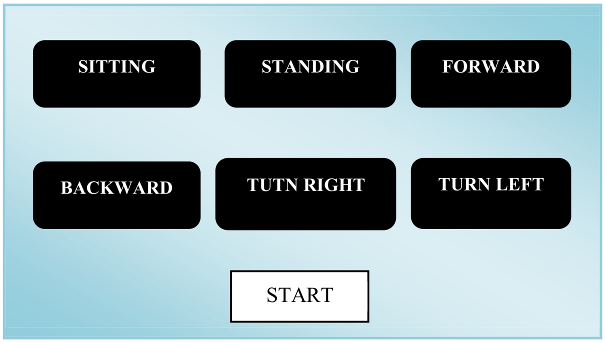


FIGURE 8. Visual stimulation interface for the different tasks.

the recorded movements. To improve the accuracy, we used SSVEP technique for brain stimulation. The visual stimulation is given by refreshing the led display using a frequency range of 6 to 40 Hz. Six different frequencies are used for six different commands. Figure 8 shows the visual stimulation interface used for implementing SSVEP. The five rounded rectangles represent the five different commands like sitting, standing, forward movement, turn right and turn left. Visual stimulation is done on the six rounded rectangles and will flick at different frequencies.

The unique features of each user movements are extracted using Walsh–Hadamard transform. The extracted features are communicated between brain and the lower limb using Bluetooth. The Hadamard coefficients along with extracted features are clubbed together for the reconstruction of original brain signal. The microcontroller in the lower limb records all the extracted information corresponding to different movements. The database is created using all the recorded user intentions. This data will be used by the microcontroller for classifying user movements.

In the online phase, the unique features of user thoughts will be co-related with the recorded features in the database. The decision making regarding required movements will be made based on the comparison result. Thus the user intentions are transferred into the actual movements on the exoskeleton. During online phase, to maintain stability and reduce faults, a particular execution pattern is designed. Table 1 indicates the command execution pattern followed in the design for better stability. The first column indicates the different commands and first row shows the current states of the exoskeleton. The design ensures that forward, right turn and left turn movements will be executed only from standing still position. The system also automatically enters the halt state whenever the movements of the body part are hindered.

D. MECHANICAL STRUCTURE AND HARDWARE DESIGN OF EXOSKELETON

The mechanical structure of the exoskeleton is designed using high torque motors with geared mechanism. Figure 9 shows the subject controlling internal part of the exoskeleton using his thoughts. This part of the exoskeleton will be encapsulated inside the designed 3D model. The 3D model along with artificial skin gives the exoskeleton the aesthetics and functionality similar to human body part. The fully functional exoskeleton system was tested and approved by an

TABLE 1. Command execution pattern.

	Sitting	Standing	Forward	Backward	Right Turn	Left Turn
Sitting	retained	executed	rejected	rejected	rejected	rejected
Standing	execute	retained	executed	executed	executed	executed
Forward	rejected	halt	retained	retained	rejected	rejected
Backward	rejected	halt	rejected	rejected	rejected	rejected
Right Turn	rejected	halt	rejected	rejected	retained	rejected
Left Turn	rejected	halt	rejected	rejected	rejected	retained

FIGURE 9. Controlling the outer structure of exoskeleton using EEG headset.

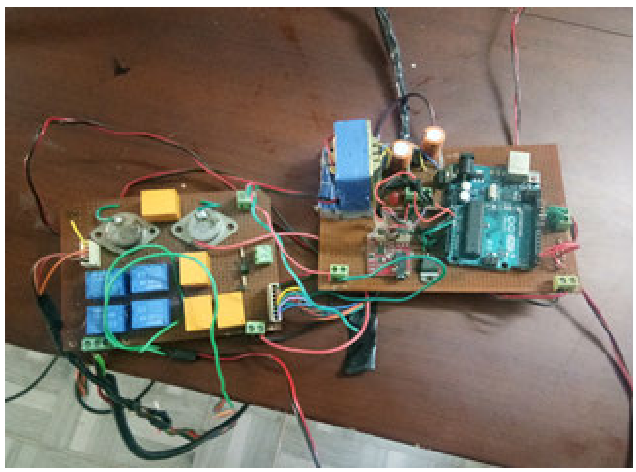


FIGURE 10. PCB of microcontroller and its associated driver circuits.

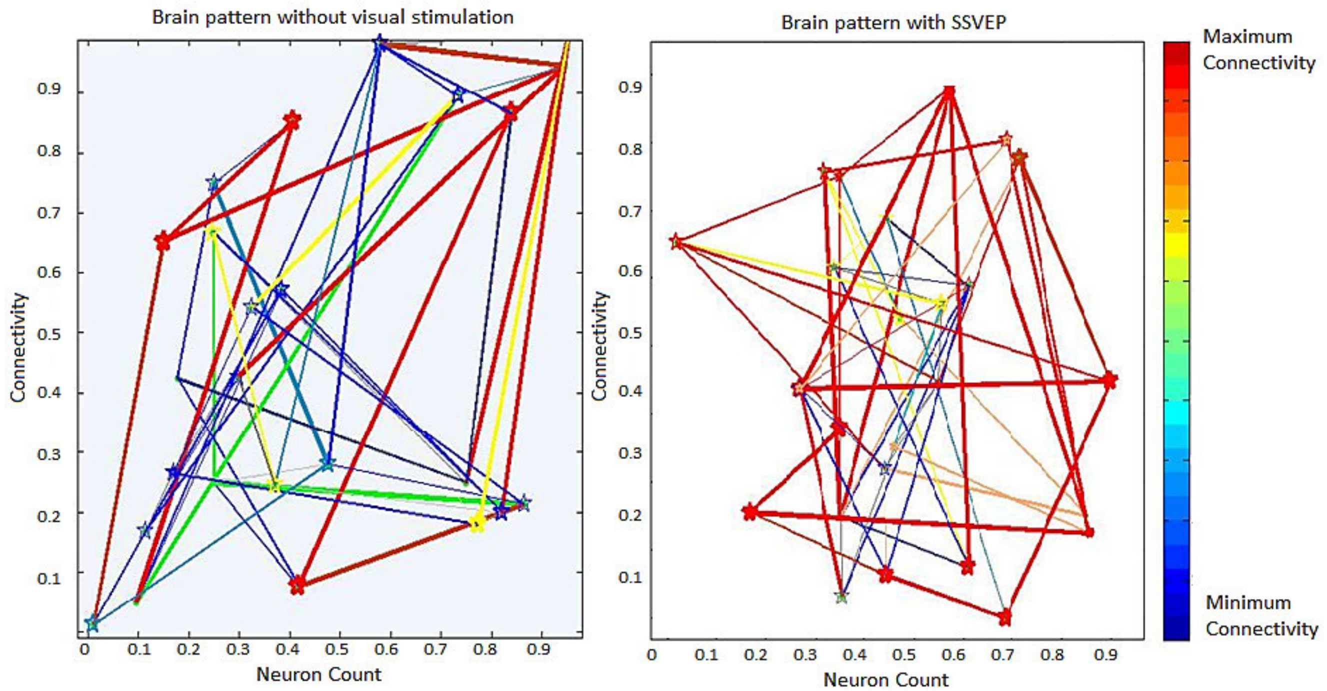


FIGURE 11. Brain Patterns with and without SSVEP.

ethics committee constituted at SCMS Group of Educational Institutions.

Figure 10 displays the PCB of the control unit and associated circuits which control all the movements of exoskeleton. Driver circuits are designed to provide enough current to activate the high torque motors and actuators. The output of the sensors integrated in the artificial skin is connected to the control unit. The PCB of control unit, driver circuits and sensor circuit will be embedded inside the exoskeleton module. After powering up, microcontroller waits for human command, based on the detected posture microcontroller activates the corresponding motor rotations. Then the microcontroller scans the sensor value to validate if the applied activation signal is sufficient to make the exoskeleton stable. According to the sensor value, alterations will be made on the excitation signal. Thus using an adaptive mechanism, system improves the stability and reduces the errors. The sensors are also utilized for providing a sense of touch. The pressure sensors accept the external force on the skin surface, converts it into vibrations with the aid of control unit. The vibrations produced on the affected body part are proportional to the applied force. These vibrations or sense of touch also assist in the rehabilitation process. Testing and validation of the hardware design are done using different human controlled movements in the online and offline phase.

VI. IMPLEMENTATION AND RESULTS

A. RESULT OF BRAIN PATTERNS WITH AND WITHOUT SSVEP METHOD

The validation of SSVEP method is done by measuring the brain patterns of the subjects with and without applying visual stimulation. Figure 11 indicates the comparison of brain patterns obtained without visual stimulation and with visual stimulation. Each node corresponds to the Neuron and connecting lines between the nodes show the neuron interaction. The red color in the figure indicates maximum interaction between neurons and the blue color indicates the minimum connectivity. The results shown in the figure indicates that, using SSVEP has improved the brain patterns or signal strength compared to brain patterns without SSVEP. The experiments are performed for different human intentions like sitting, standing, forward, backward, turn left, turn right, etc. Blue color represents minimum connectivity and red color represents maximum connectivity. Results from the figure show that without visual stimulation the brain patterns or signal strength corresponding to human thought is minimum. The number of neurons involved in thought processing is also reduced. To reduce visual fatigue, high-frequency greater than 30 Hz is used for visual stimulation.

The offline and online experiments are conducted on four healthy subjects and two paralyzed persons. In the offline phase the EEG signals corresponding to different movements are acquired using 14 channel EEG sensor. The WHT is applied to compress a large amount of EEG signal in order to save the storing space. The WHT does a fast computation of the WHT coefficients and stores only the frequency coefficients having large magnitude. These coefficients are used for the accurate reconstruction of original signals. The signal energy is concentrated at lower frequency value so that higher frequency coefficients can be removed to suppress the noise. In the online phase,

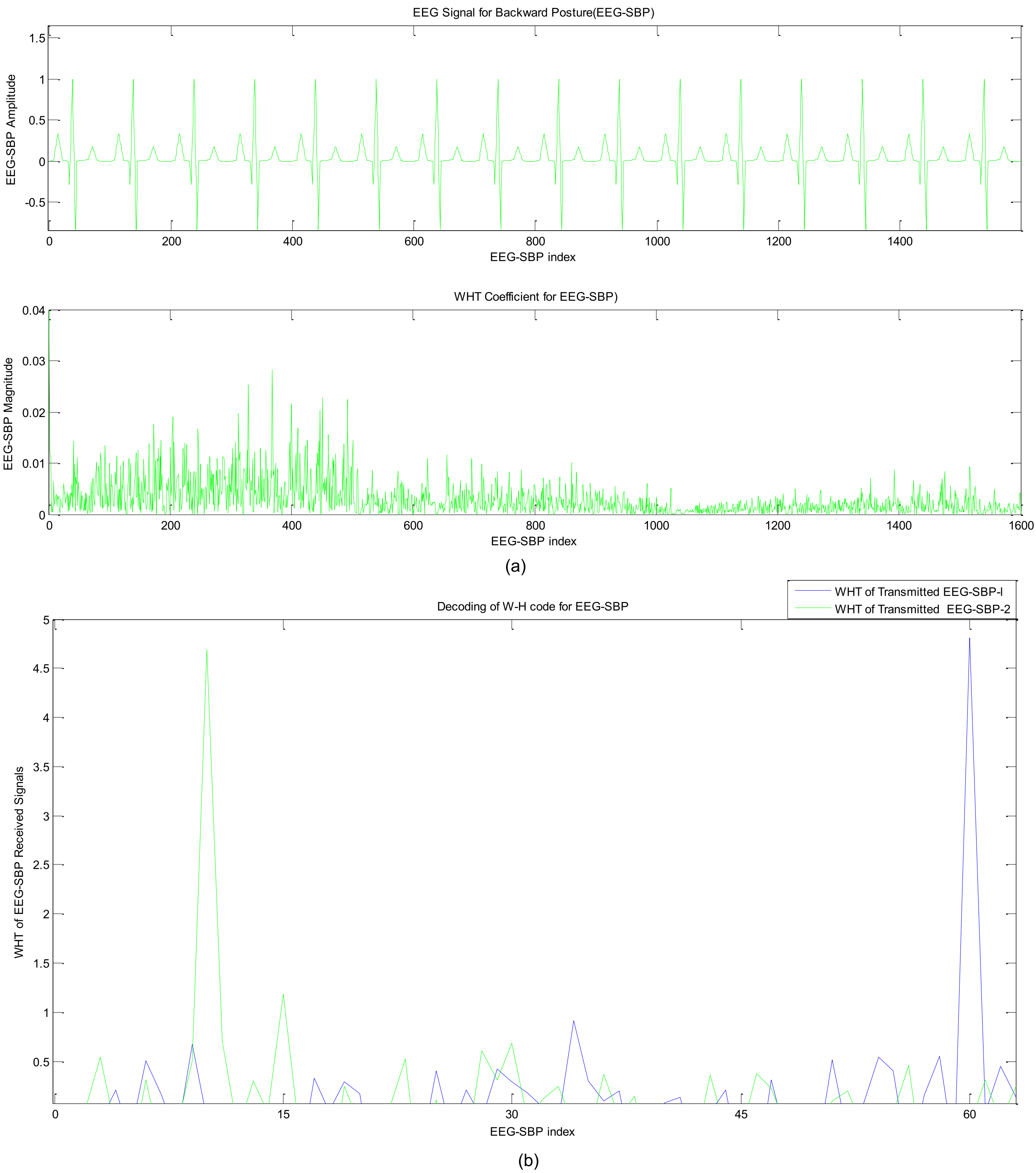
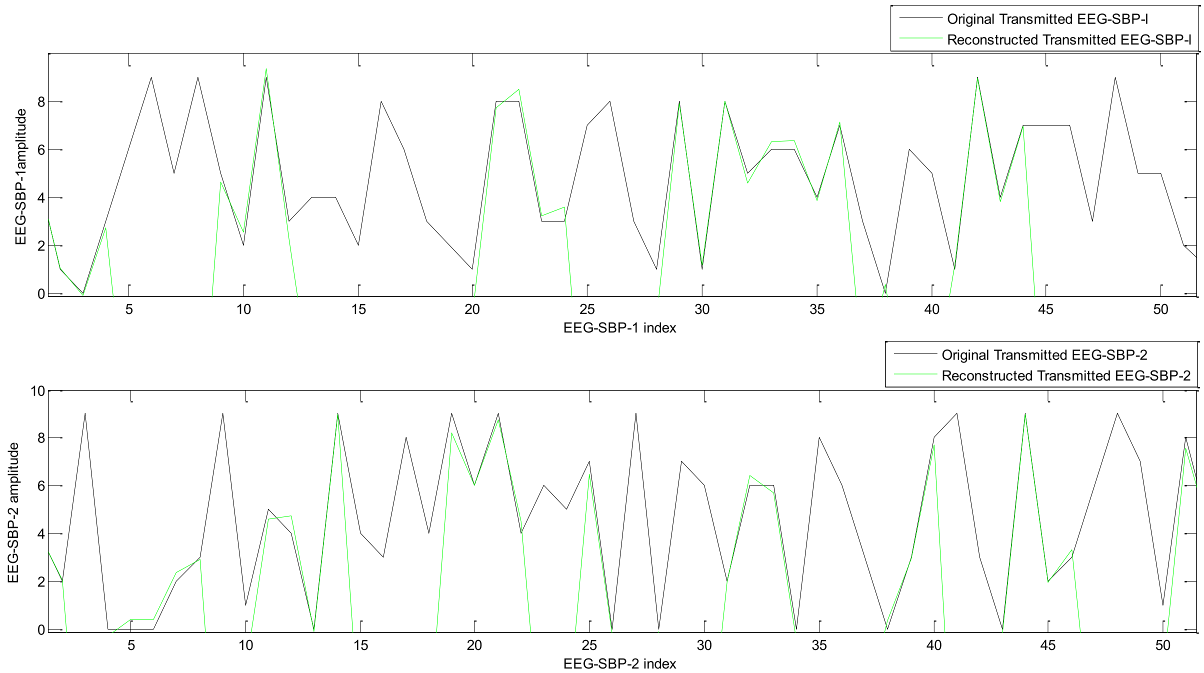


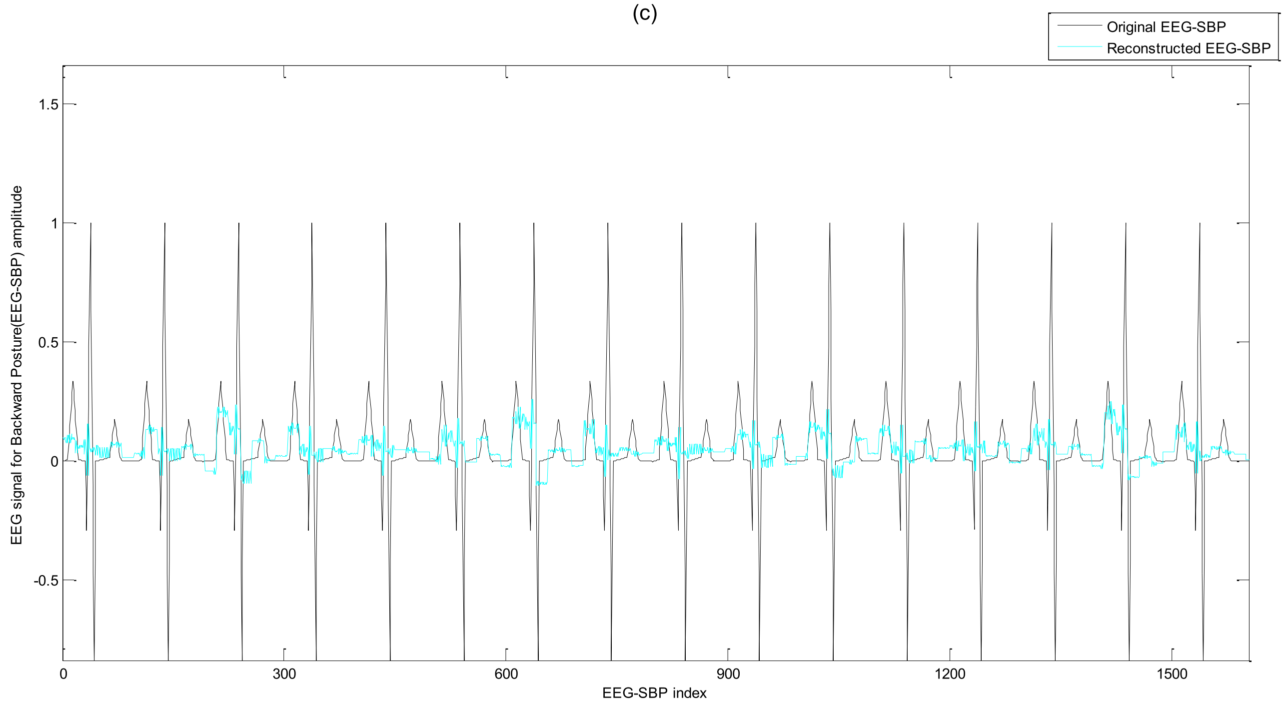
FIGURE 12. Reconstruction process of EEG signal using WHT corresponding to Backward movement.

the extracted features and WHT coefficients are transmitted from brain to lower limb for the reconstruction of original signals. The results of the feature extraction and signal reconstruction of six different thoughts are depicted in Figures 12 to 17.

Figure 12 shows the EEG patterns corresponding to the backward movement. It has six sub figures showing EEG patterns captured, WHT coefficients, Transmitted WHT coefficients, Original and Reconstructed EEG signals under two different time instances designated as EEG-SBP-1 and EEG-SBP-2, Final original and reconstructed signal. Figures from 13 to 16 indicate the EEG signal reconstruction of four different human intentions such as Forward movement, Sitting, Standing and Turn Left. Figure 17 shows the



(c)



(d)

FIGURE 12. ***(Continued.)*** **Reconstruction process of EEG signal using WHT corresponding to Backward movement.**

measured EEG pattern, WHT coefficients and the reconstructed signal.

B. STATISTICAL ANALYSIS OF MEASURED EEG PATTERN

Statistical analysis of the measured EEG signal is carried out to determine the correlation between original and reconstructed signal. The data obtained during the backward and forward movements performed by the user is utilized for the analysis. Correlation matrix is calculated between original and reconstructed waveforms.

Here the correlation coefficient is calculated and obtained as, Corrcoef (x1, xHat1)

$$\begin{bmatrix} 1.0000 & \cdots & 0.0867 \\ \vdots & \ddots & \vdots \\ 0.0867 & \cdots & 1.0000 \end{bmatrix}$$

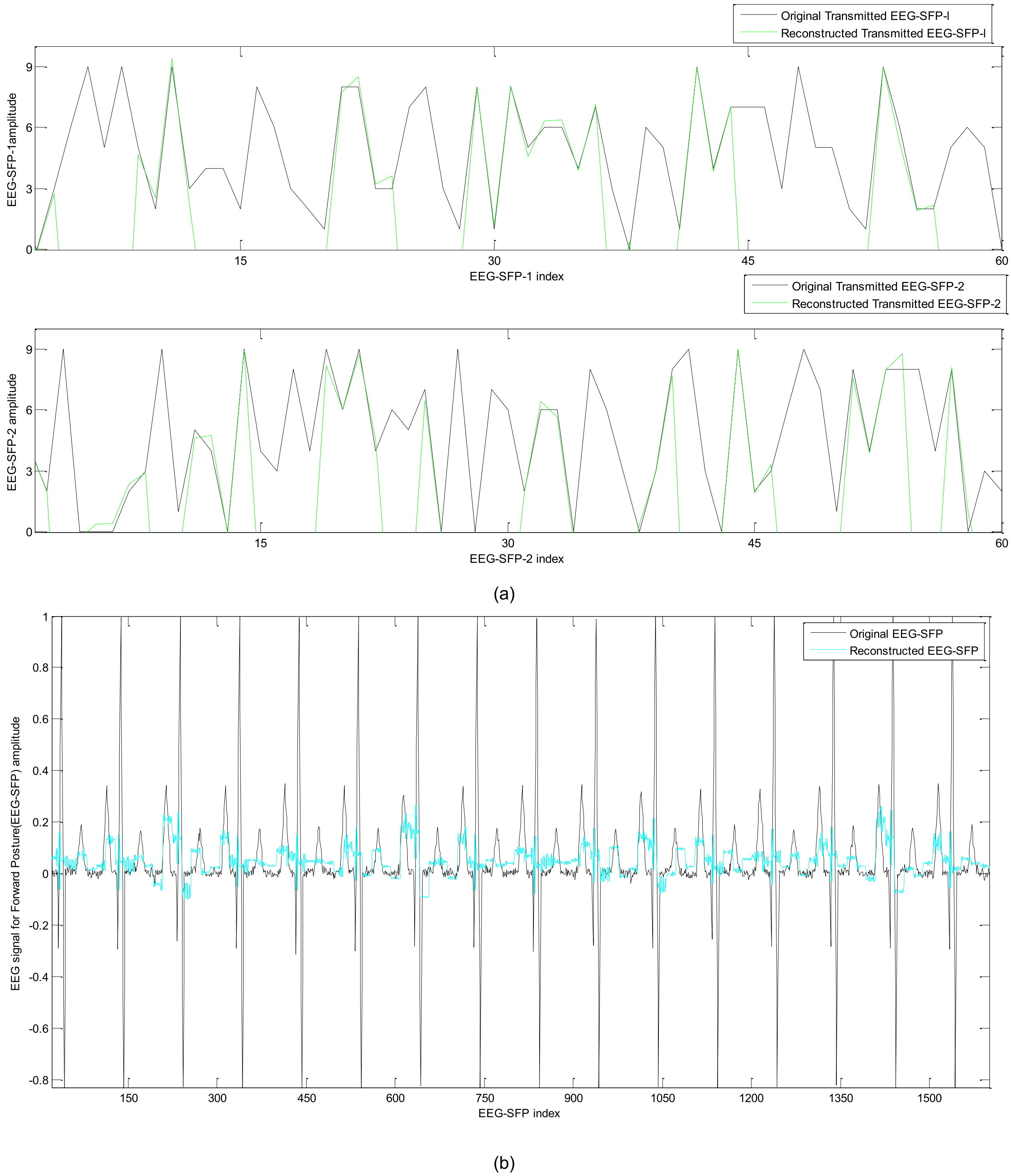


FIGURE 13. Reconstruction process of EEG signal using WHT corresponding to Forward movement.

Here the correlation coefficient is calculated and obtained as, Corrcoef(x2, xHat2)

$$\begin{bmatrix} 1.0000 & \cdots & -0.0640 \\ \vdots & \ddots & \vdots \\ -0.0640 & \cdots & 1.0000 \end{bmatrix}$$

Based on the statistical analysis it is clear that there is correlation between original and reconstructed signal, but the miss match in the graph is due to the phase shift introduced by the amplifiers.

C. RESULTS OF CLASSIFICATION ACCURACY OF DIFFERENT SUBJECTS

The classification accuracy of the system is verified by performing the test on ten healthy subjects and ten paralyzed persons. The maximum obtained is 87% efficiency and on

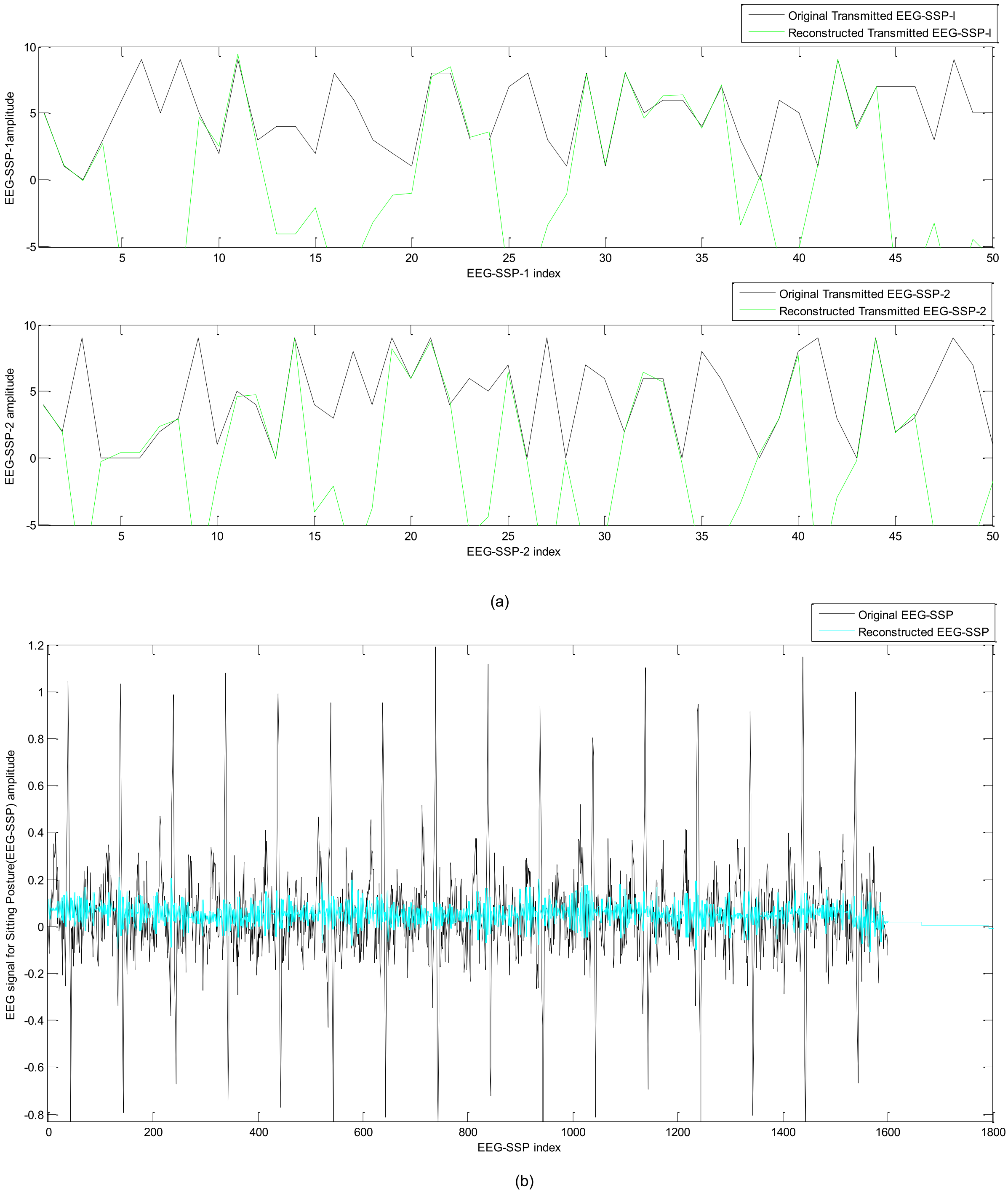
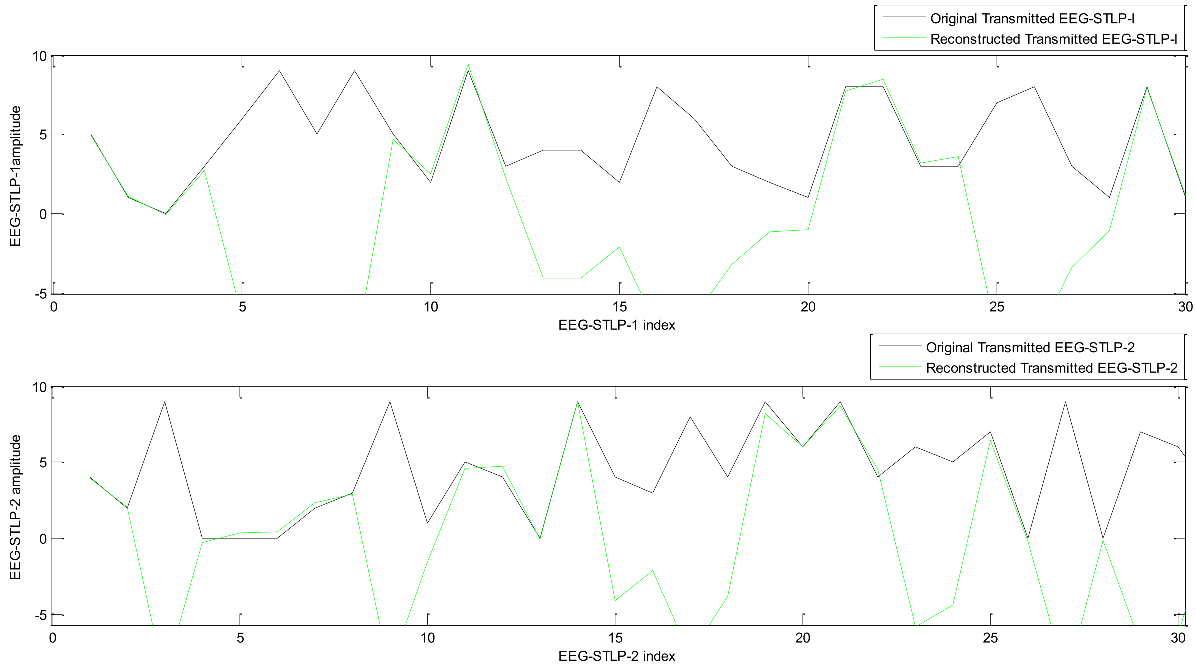


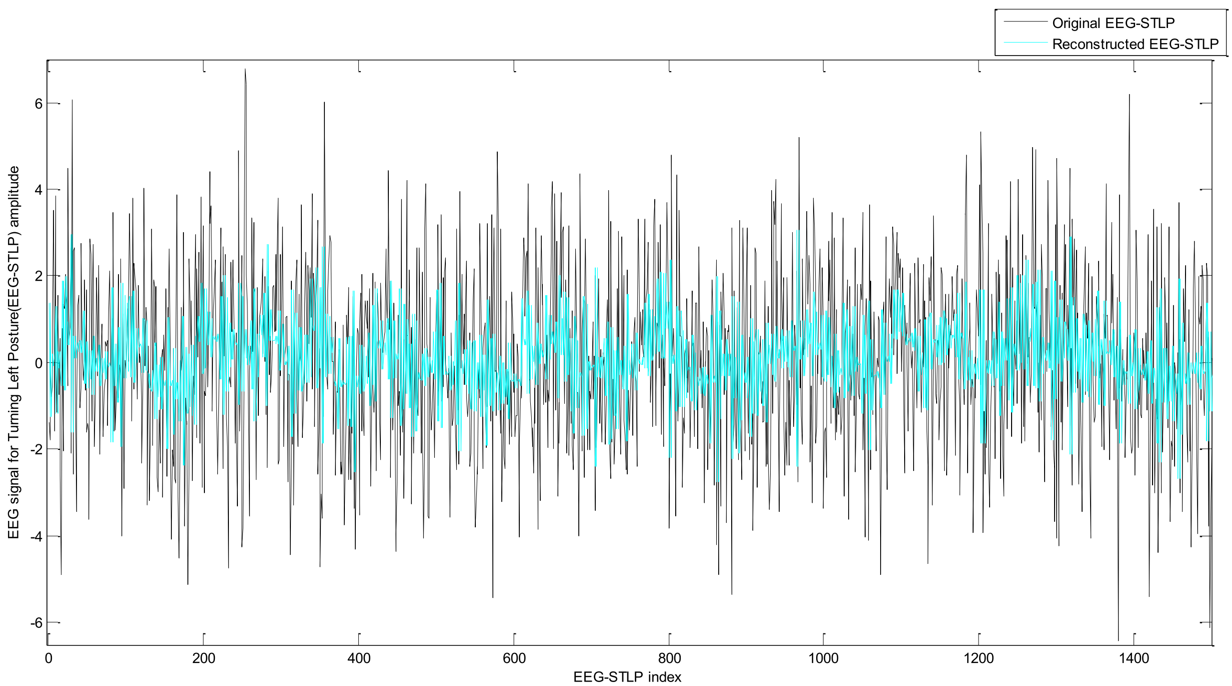
FIGURE 14. **Reconstruction process of EEG signal using WHT corresponding to Sitting Posture.**

an average 80% classification accuracy based on the five different human intentions. The experimentation result shown in Figure 18 is the summary of results on six participants. U1, U2, U3 and U4 represent healthy subjects, U5 and U6 represent paralyzed persons. The results of classification accuracy on the different commands are depicted in Figure 19. The reason for improved accuracy for classification among subjects is due to intensive and systematic training undertaken. The healthy subject u2 is an experienced user and is more familiar with similar interfaces, obtained high accuracy. However, the unhealthy subjects U5 and U6 also obtained high accuracy through their dedication and passion.

Visual stimulation and voice assistance are also given to paralyzed during training. The participants U1 and U4 have shown similar low classification accuracy due to their age and unfamiliarity with the system.



(a)



(b)

FIGURE 15. Reconstruction process of EEG signal using WHT corresponding to Standing Posture.

D. RESULTS OF EEG PATTERNS USING REALISTIC HEAD MODELS

EEG analysis is carried out using realistic Head models to identify the unique EEG signal features and to validate the brain network connectivity. EEG signal is acquired by 16 electrodes placed in the frontal and parietal regions of the Brain. Figure 19 indicates the electrode placement scheme followed in the experimentation.

The electrodes E12, E5, E13, E6, and E7 are placed in the parietal region and remaining in the frontal region, as shown in Figure 19. The power spectral analysis is carried out for each electrode used in the signal acquisition,

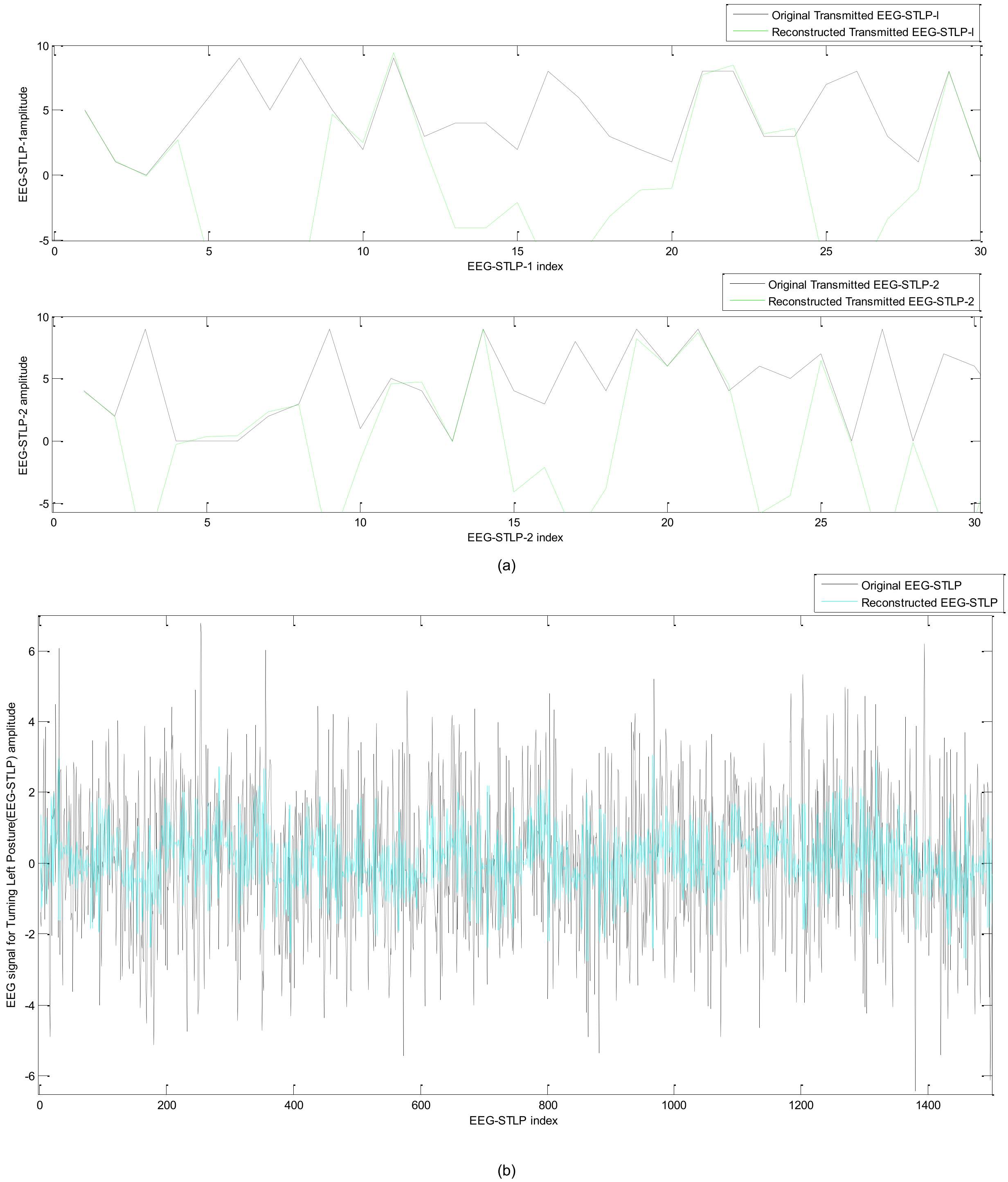


FIGURE 16. Reconstruction process of EEG signal using WHT corresponding to Turn Left Posture.

Figure 20 indicates the brain patterns variations at different frequencies based on power spectral density.

The brain signal analysis using realistic head model is carried out for different human intentions and on variety of healthy and unhealthy subjects with repeated trials. Figure 21 depicts the realistic head models with active and non-active region variations.

These simulation results are used for the EEG source estimation using conventional estimation approaches. The estimated sources are further used for the calculation of position and Energy Index. The simulated scalp EEG signals are then used for the reconstruction process of the original signal at the receiver. The validation of SSVEP method is also done using realistic head models.

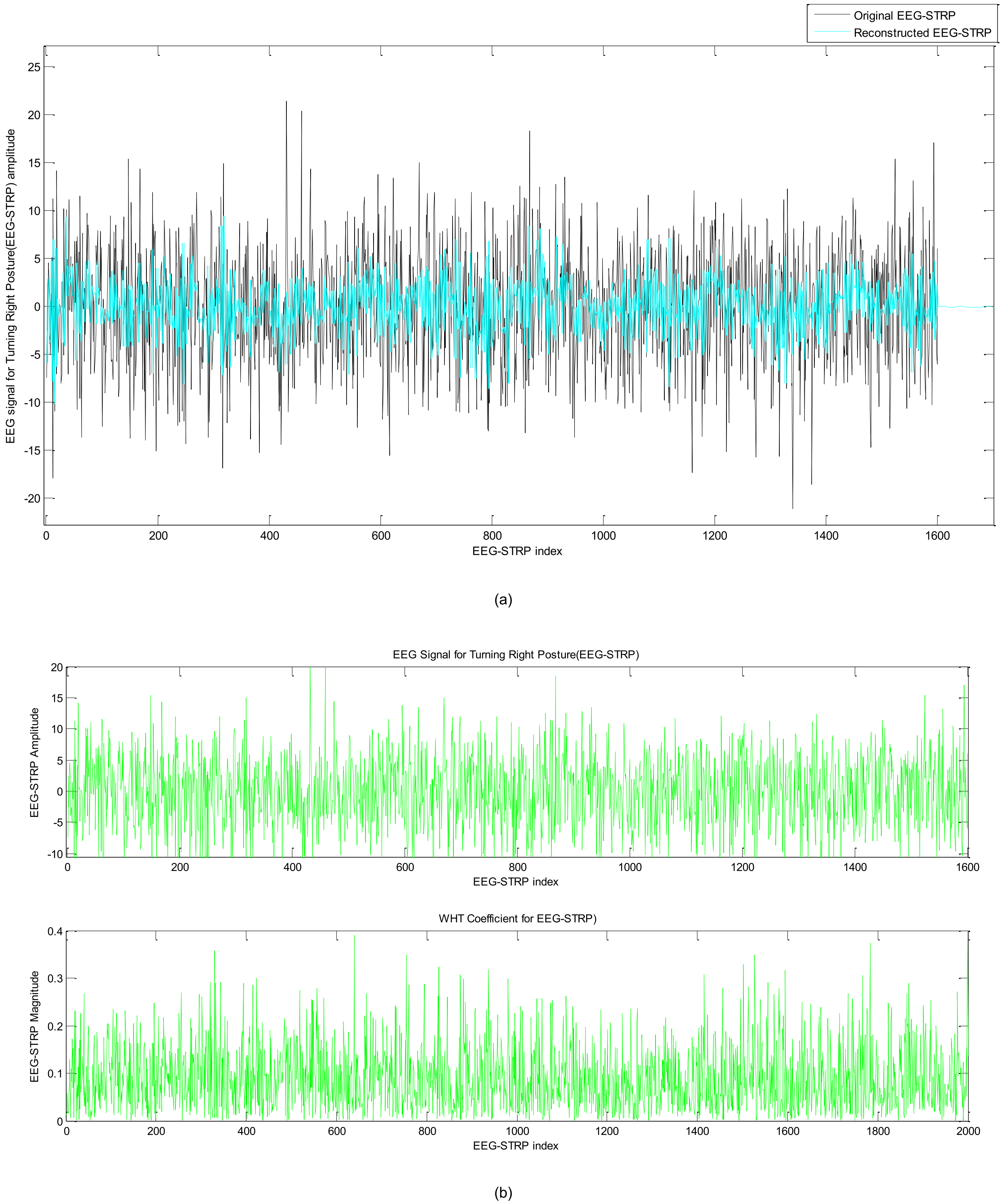


FIGURE 17. **Reconstruction process of EEG signal using WHT corresponding to Turn Right Posture.**

Figures 22 and 23 shows the comparisons of head models with and without application of the SSVEP method. In the figure, red color indicates maximum interaction between neurons, yellow indicate moderate and blue indicates minimum connectivity. Hence the result indicates that using SSVEP has improved the concentration level of the subjects

Figure 24 depicts the power spectrum corresponding to human intention for forwarding movement. The power spectral analysis is carried on the different brain patterns to

TABLE 2. Data statistics for SBP-1 original signal.

Parameters	X variable	Y variable
Min	1	0
Max	64	9
Mean	32.5	4.734
Median	32.5	5
Mode	1	5
Standard deviation	18.52	2.773

TABLE 3. Data statistics for SBP-1 reconstructed signal.

Parameters	X variable	Y variable
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 SFP-1 original signal.

Parameters	X variable	Y variable
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 SFP-1 reconstructed signal.

Parameters	X variable	Y variable
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

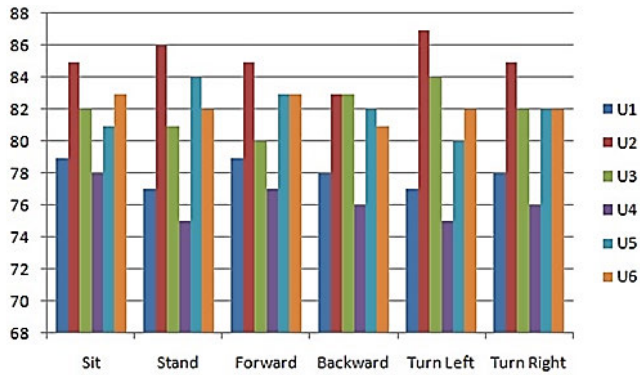


FIGURE 18. Classification accuracy of different commands.

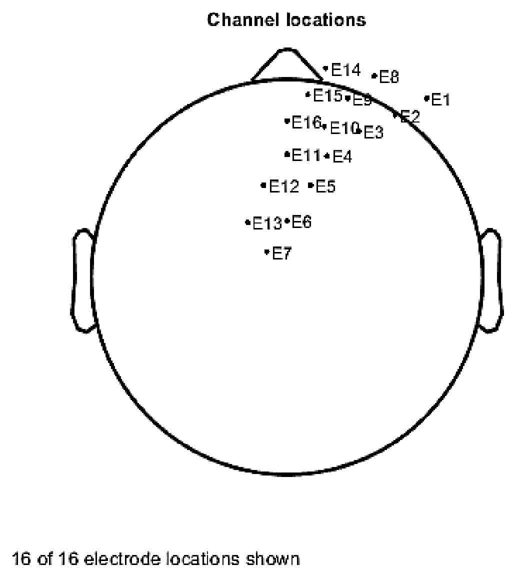


FIGURE 19. Location of 16 different electrodes.

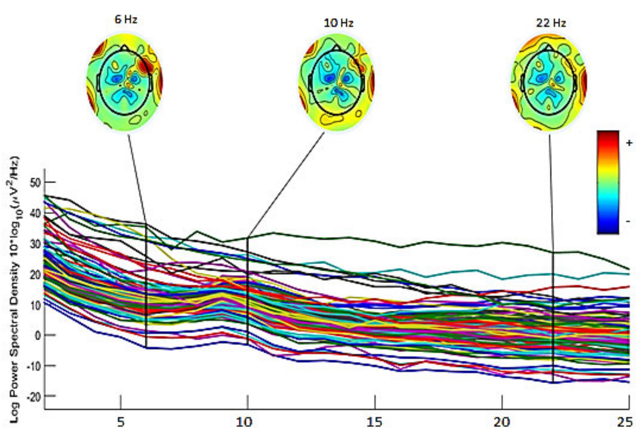


FIGURE 20. Brain pattern variations at different frequencies.

identify the signal strength and variations of signal with respect to the frequency. These extracted signal characteristics are utilized for improving the classification accuracy.

Statistical analysis is performed on the data obtained using each EEG channel. Figure 25 indicates the statistical parameters obtained for channel 1. The graph shows the correlation between acquired data and standard normal values.

The effectiveness of REST with respect to AR is analyzed through simulations using realistic head models. Coherence and network connectivity are calculated for the same 16 electrode scheme for a particular human thought. Figure 27 shows the coherence and connectivity obtained for particular human thought. Figure 27(a) depicts EEG recording using REST

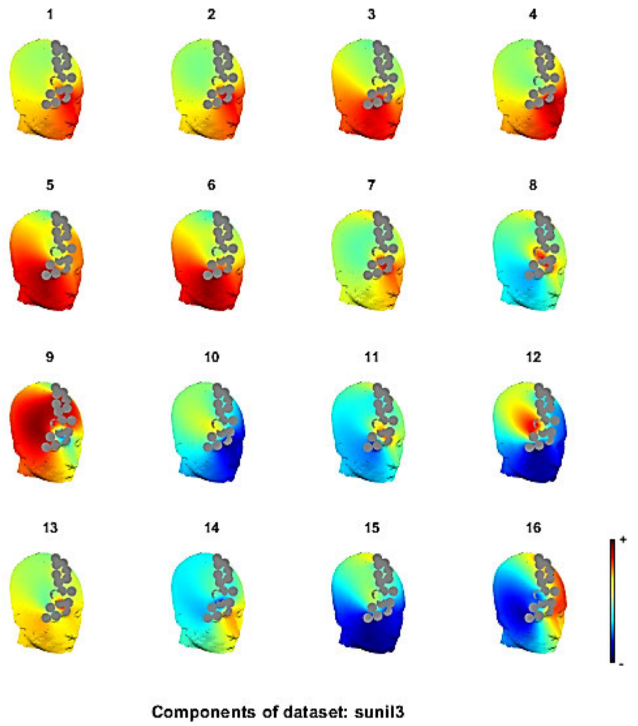


FIGURE 21. Realistic head model with active region.

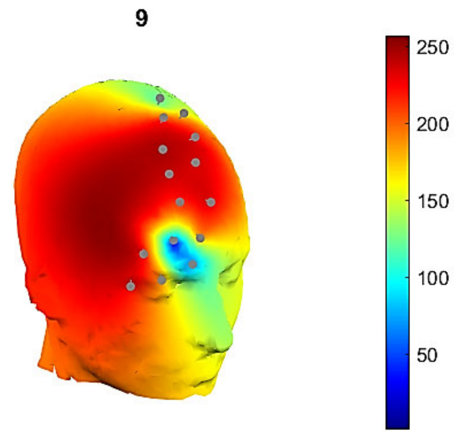


FIGURE 22. Realistic head model of the subject with SSVEP.

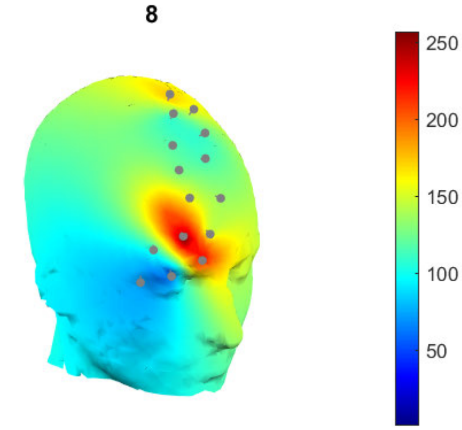


FIGURE 23. Realistic head model of the subject without SSVEP.

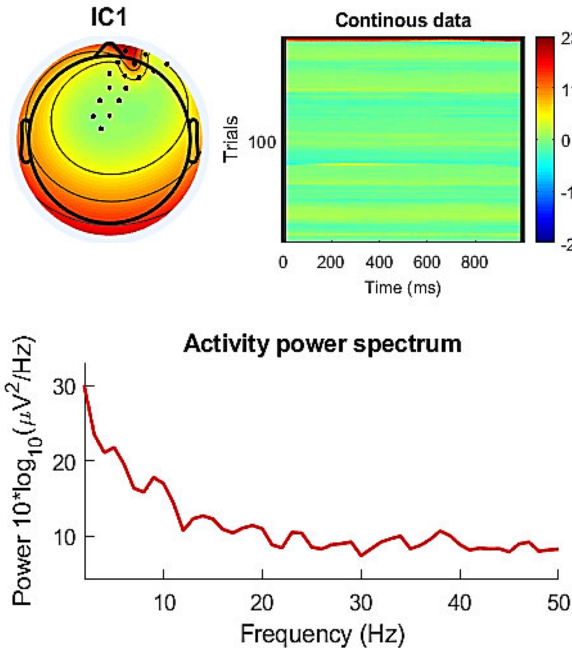


FIGURE 24. Power spectrum of human intention for forwarding movement.

Referencing method and 27(b) indicates EEG recording using AR referencing method. Simulation results show that REST referencing provides better connectivity and coherence compared to AR.

VII. DISCUSSION AND SUMMARY

The authors used EEG signal to identify the human Intentions and to control the body parts using unique exoskeleton, which is convenient to carry for the user to perform routine activities.

A. PREVIOUS STUDIES

Iturrate *et al.* [26] used neuro Rex exoskeleton with BMI capabilities to assist people with mobility impairments. The study evaluated health benefits of using exoskeleton and showed that BCI based exoskeleton control is an effective method. Guan *et al.* used motor imagery based EEG to detect and classify human intentions and obtained a classification accuracy of 79.8% [27]. Gait phase prediction algorithms are successfully implemented to improve the lag motions [28]. However, the exoskeleton is bulky and prediction accuracy was only 69.8 %.

B. NOVEL CONTRIBUTIONS OF THIS RESEARCH

The classification accuracy is improved in our research by using SSVEP method. Flexible exoskeleton models are designed, which can be used for people with different levels of disability. The use of carbon film material for the construction, made it low weight and easy to configure. Moreover, the fall detection and sensory feedback are incorporated for better safety of the user.

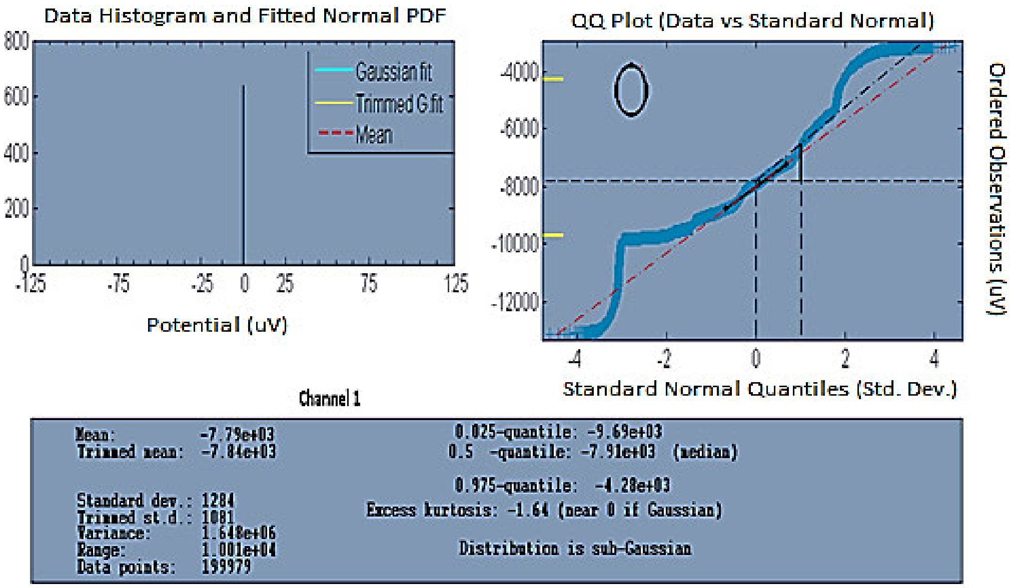


FIGURE 25. Statistical data analysis for channel 1.

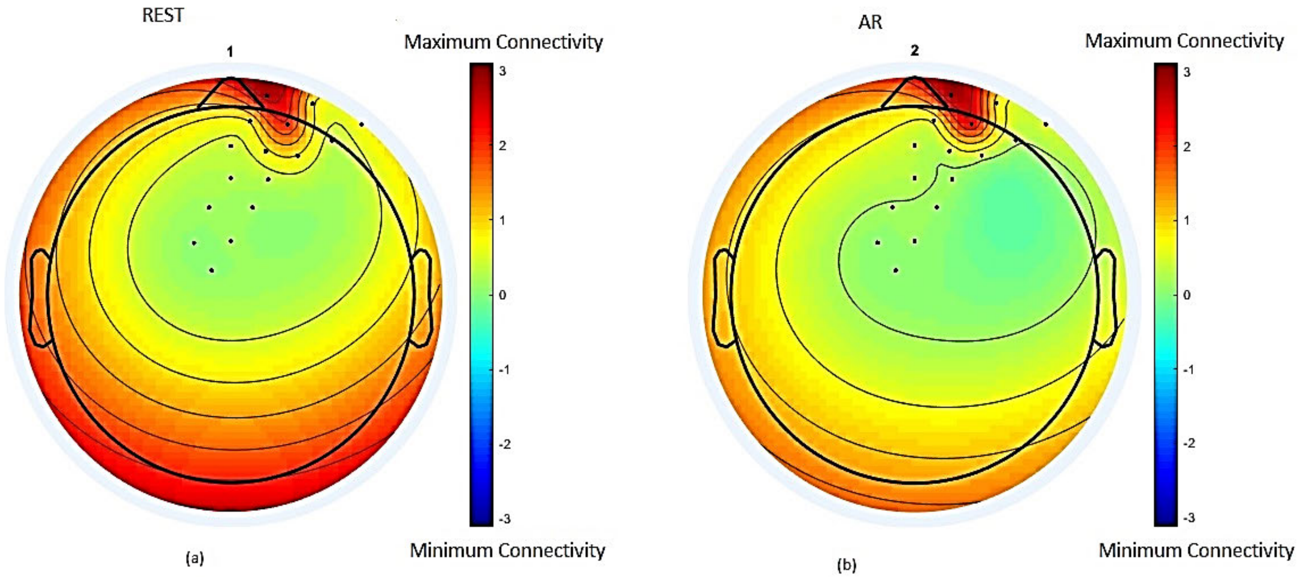


FIGURE 26. Comparison of REST and AR referencing Methods.

C. LIMITATIONS AND FUTURE RESEARCH SCOPE

The sensors with high precision are very expensive and the head set is causing in convenience to the user. The future research should focus on reducing human workload by incorporating efficient controllers. Developing exoskeleton with machine leaning algorithms that can match human intentions are the way forward

VIII. CONCLUSION

A Brain-Controlled Lower-Limb Exoskeleton (BCLLE) with unique structure and flexibility is designed. Online and offline testing of the BCLLE on six different subjects was carried out. WH Transform is utilized for feature extraction and reconstruction. The results obtained indicate that it produces good classification accuracy. SSVEP method is incorporated using a visual interface, which improved human concentration. The healthy and paralyzed subjects were able to control the exoskeleton for different movements such as backward movement, forward movement, Sitting, Standing, Turn Left and Turn Right. The sensory feedback was implemented using angle sensors and rescue assistance is provided using accelerometers. The adaptive mechanism used helped to reduce the false rate of the system. The secure message transmission is established using NTSA encryption, which helped the caregiver to know the status of the paralyzed. In our future work, we will be designing a full body exoskeleton compactable for the entire body and also customizable for affected body parts. Machine learning approaches will be incorporated to improve the classification accuracy in the online phase.

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