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Preliminary Study on Brain Computer Interface

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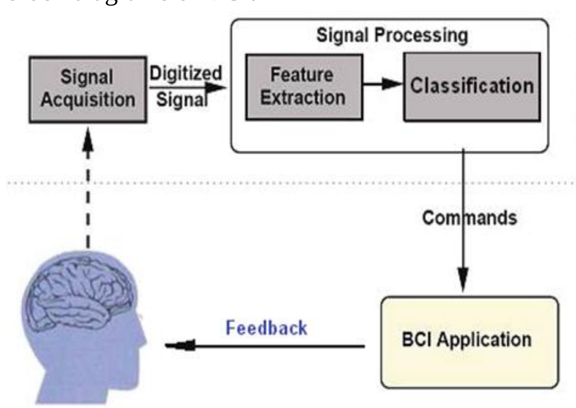
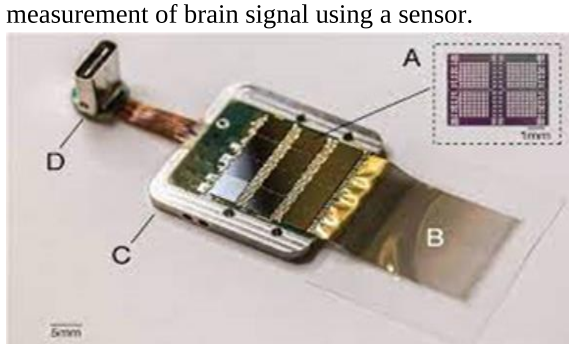
***Abstract* - Brain Computer Interface (BCIs) acquire brain signals, analyze them, and translate them into commands that are relayed to output devices that carry out desired actions. BCIs do not use normal neuromuscular output pathways. The main goal of BCI is to replace or restore useful function to people disabled by neuromuscular disorders such as amyotrophic lateral sclerosis, cerebral palsy, stroke, or spinal cord injury. From initial demonstrations of electroencephalography-based spelling and single-neuron-based device control, researchers have gone on to use electroencephalographic, intracortical, electrocorticographic, and other brain signals for increasingly complex control of cursors, robotic arms, prostheses, wheelchairs, and other devices. Brain-computer interfaces may also prove useful for rehabilitation after stroke and for other disorders. In the future, they might augment the performance of surgeons or other medical professionals. Brain-computer interface technology is the focus of a rapidly growing research and development enterprise that is greatly exciting scientists, engineers, clinicians, and the public in general. Its future achievements will depend on advances in 3 crucial areas. Brain-computer interfaces need signal-acquisition hardware that is convenient, portable, safe, and able to function in all environments. Brain-computer interface systems need to be validated in long-term studies of real-world use by people with severe disabilities, and effective and viable models for their widespread dissemination must be implemented. Finally, the day-to-day and moment-to-moment reliability of BCI performance must be improved so that it approaches the reliability of natural muscle-based function.**

INTRODUCTION

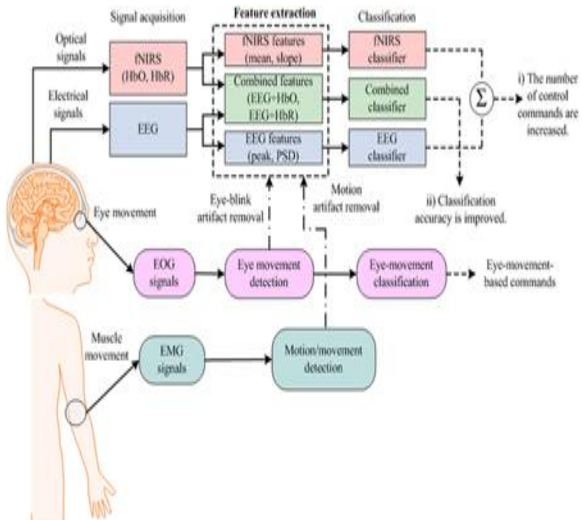
Brain Computer Interface (BCI) is a system that measure activity of the central nervous system and convert it into artificial output BCI. Improve many functions of human including replace lust function such as speaking or moving they also may restore the ability to control the body such as by stimulating nerves or muscles that move the hand. BCI utilize many techniques for measuring the brain activity such as electroencephalography (EEG), Functional Magnetic Resonance Imaging (FMRI)- which exploit the changes in the magnetic properties of hemoglobin as it carries oxygen, Magneto encephalography (MEG), Electrocardiography (ECOG), etc. Basic block diagrams of BCI.



Signal Acquisition unit in BCI helps in the measurement of brain signal using a sensor.



The sensor is basically a device implanted in the brain usually multi-electrode arrays that record the signal directly related to the movement, the amplitude of brain signal is very much smaller in (micro or mille) so it has to be amplified with a suitable amplifier to level suitable for electronic processing and the filtered signal can digitized and transmitted to a computer.
After this the digital signals are analyzed by feature translation and translate into output command commands.



There are three main types of BCI, which the electrical signals that pass between neurons and translate them to a signal sensible by electronic device.

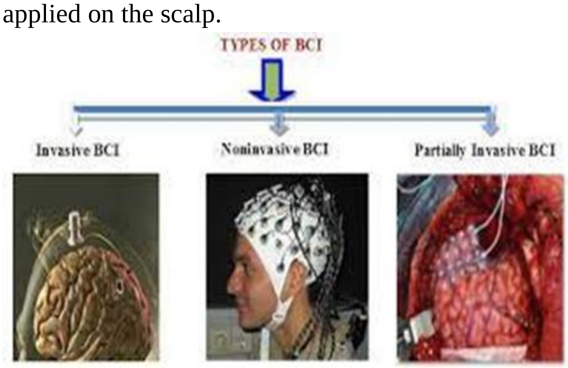
Invasive (BCI) – Electrode are implanted directly into the gray matter of the brain during neurosurgery just like a device name N1 Link created by Neuralink a biggest company in this field, this N1 Link is directly implanted into the gray matter ,the N1 Link contains 96 hairs like structure in one electrode and there are total 32 electrode in this link , which make 3072 channels(Neural Threads) that's large number of channel make it produce the highest qualities signals, but here also several problems occur because brain think it as a unnecessary material come inside it which is not part of it.

B – contains the hair like structure

LINK

Partial invasive – It is another brain signal reading process which is applied to the inside of skull but outside the gray matter,

Non-invasive – In this process medical scanned devices or sensors are applied outside of the just applied on the scalp.



Applications

Brain Activity Measurement- In most of the hospital in monitoring the brain activity they use the EEG technique, they keep electrode cap on the head and they will monitoring electrical activity of the brain and they will seen it in a form of monitor and according to electrical activity they treat the patient.

Robotics – Distinct kind of electrical activity happening inside our brain neurons, by grabbing those electrical activity or signals we can able to identify that we are blinking and we can give the command to some of the machine to work.

Artificial Intelligence – with the help of BCI and AI, we can create an animal sense a sensation which it normally does not sense.

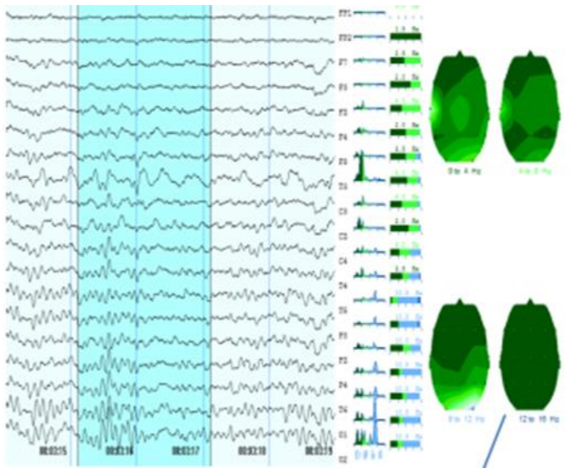
Rehabilitation – There several rehabilitation centers in India, in these centers people which are addict of something like drugs or anything else are treated according to their brain activity.

This is not only, through BCI the peoples lost their eyesight would be able to see, those who can't hear could hear the voice of their relatives again, paralyses people would be able to control smart phones, computer and would be able to share their thoughts with the world, people could also be able control the games, drones, robots their minds and also they would we able to light the bulb just by blinking their eyes.

BCI – Controlling Devices Utilizing the Alpha Brain Waves

The response generated through the movement of the eye (detecting and controlling the amplitude of the alpha brain waves) is interfaced and processed to control robotic system and smart home control. The major reason why the Alpha waves are used instead of Delta, Beta, Theta waves is simply because these waves can voluntarily and easily be controlled by paralytic people to gain motor control.

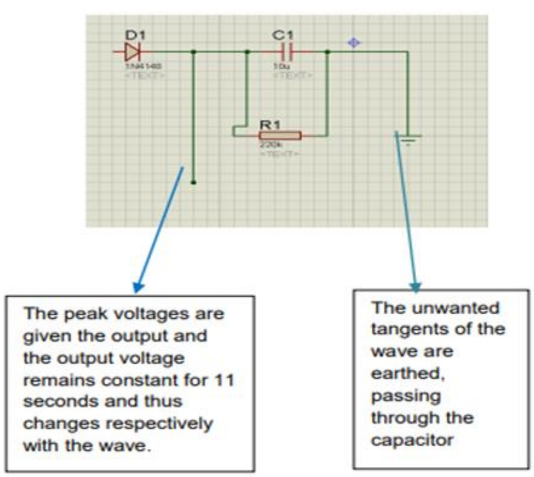
Over 32 regions of the Brain lobes the brain signals were measure and conclusion came that maximum Alpha waves are generated over the region of Fp2, O2an eye closure. If we depict the brain waves over the region we depict change in color over the occipital region.



(Depicts the brain waves over regions and also shows the frequency spectrum maps over these regions)

Using the electrode near the mastoid region (AI) because this electrode is used as a reference electrode with absolutely zero potential so as to act as differentiating electrode for the other two electrode places. To amplify the voltage AD620 instrumentation amplifier is used to obtain a gain of 22455. The AD620 comprises three operational amplifiers.

At First each amplifier 1 and 2 amplifies the voltage input individually and the net amplified voltage it further amplified by amplifier three and thus the final voltage output is obtained. Due to external noise raging (45-65) Hz, we use a (9-12) Hz Band Pass filter. Due to rapidly change in Brain waves we calculate the rate of waves at peak which is measured by devising a Peak-to-Peak detection circuit, by charging the plates of capacitor, the plates do not allow the peak voltage to pass and thus send them as output.



(Circuit of the peak to peak detector with 11 Seconds of peak consistency)

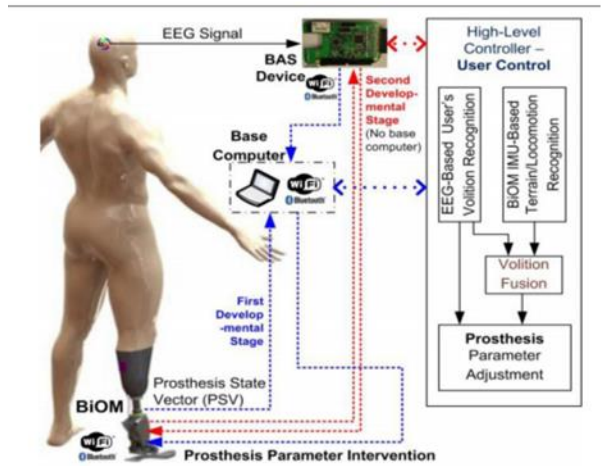
By using the Arduino Uno microcontroller and programmed Alpha waves in such a way that a varied input of amplitude of alpha waves different devices could be controlled.

With reference do the analysis of the data over the subjects it is quite possible to use Alpha Brain waves like a switch or a trigger to gain control over the electronic devices.

Electroencephalogram- Based Brain- Computer Interface and Lower Limb Prosthesis Control: A Case study

People who have received limb – amputation face staggering emotional and financial lifestyle changes. They require one or more prosthetic devices and services, which must be maintained for rest of their lives.

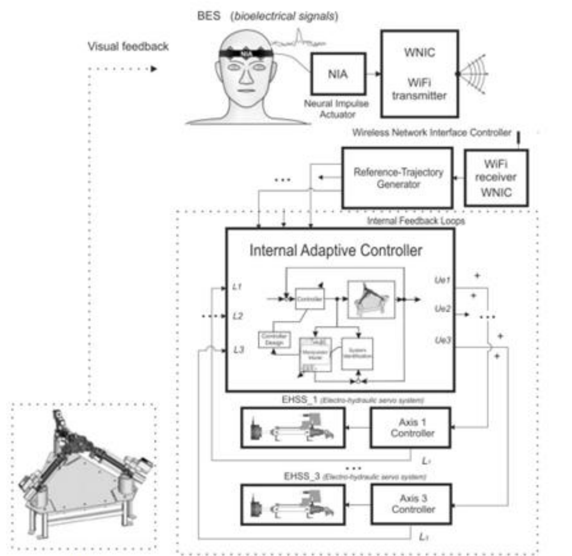
A transfemoral amputee subject was trained to activate knee – unlocking switch through motor imagery of the moment of his lower extremity. Surface scalp electrodes transmitted brain wave data to a software program that was keyed to activate the switch when the event – relate desynchronization in EEG reached a certain threshold.



Using an ADS -1299 module greatly reduced the cost of the Brain Board, while maintaining high quality amplification. A 32-Bit MPU (AT32 Atmel AVR Microcontroller) was embedded in the Brain Board for onboard real –time signal processing and data transmission. After achieving more than 90% reliability for switch activation by EEG rhythm-feedback training, the subject then progressed to activating the knee-unlocking switch on a prosthesis that turned on a motor and unlocked a prosthetic knee. The frequency band was determined by the ERD analysis of cued motor task. The EEG signals were then band passed (1–100 Hz) using a custom-made MATLAB tool box (BCI2VR). The ERD of the beta band (16–24 Hz) was calculated in real time against baseline activity when the subject was relaxed. Four training session occurred on four separate visits and were conducted before the trial. Each session lasted about 1.5h (excluding the time for EEG setup). The subject walked back and forth in the parallel bars and unlocked the knee for swing phase and for sitting down. A transfemoral prosthesis which is a well-fitting ischial containment socket, with gel seal-in suction liner for suspension, a modular single axis knee joint, with lock and extension assist (Otto Bock 3R33) and a solid ankle cushion heel foot, was modified with a rotary actuator that was controllable through a BCI system. The success of knee unlocking through this system was measured.

Brain- Computer Interface for control of eletrohyd-raulic servo drive.

The aim of the study was top perform bioelectric signal analysis focusing on is applicability to control of the electro-hydraulic servo drive. Stimulating muscles, eyeball movement or a bioelectrical change in the brain activity causes a change in people biopotential which may be measured and used as a control signal. A Wireless Network Interface Controller (WNIC) was built to test the use of bioelectric signal and wireless communication in the control of electro-hydraulic position system. The control operator has a band on their head with three electrodes, which record bioelectrical signals generated by the brain, face and eye muscles. The signals are then enhanced by the Neural Impulse Actuator (NIA), fed into a Wireless Network Interface Controller (WNIC) and analyzed by appropriate software which is included with the device. The software generates control signals which are passed onto the application responsible for the controller-computer communication. Data between the computer and the controller are sent via a wireless IT network. On the basis of the value of the intended actuator position received from the operator and the current position the controller generates appropriate control signals. The current actuator position is sent to the operator in order to verify the intended position. The NIA device by OCZ is a BCI (Brain-Computer Interface) type interface equipped with a neurosignal reader. The signals originating from the neural activity of the brain are captured by NIA in the form of electrical biopotentials which occurred as a result of Alpha and Beta brain waves, movement of the facial muscles and eye lids. Effective control of technical devices with the use of NIA requires a snug fit of the brain wave reader sensors to the forehead, calibration of the device and training. A dedicated application analysis of EEG, EMG and EOG bio signals together with one basing on appropriate bioelectric signal values as defined by the user, generate signals for pressing keys in the keyboard.



The electro-hydraulic positioning system using the bioelectrical signals (BES) and a wireless network interface controller (WNIC)

The bio signal can have both positive and negative voltage. The resulting bio signal can be processed to eliminate noise or other possible interference. Due to very low amplitude of the bioelectrical signal a suitable amplifier is used which amplifies the signal and make it useful control signal. The precision of position control of the eletro-hydraulic servo derive may be increased by the operator undergoing appropriate training.

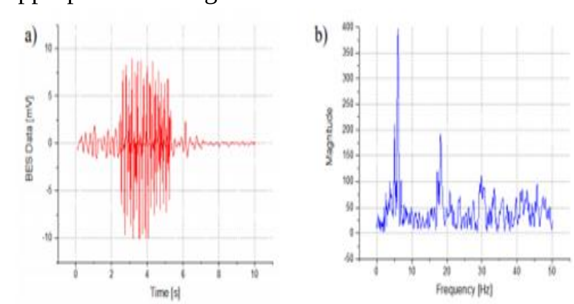


Fig. 6. Generating characteristics of a single channel signal (a) using a frequency analysis (b)

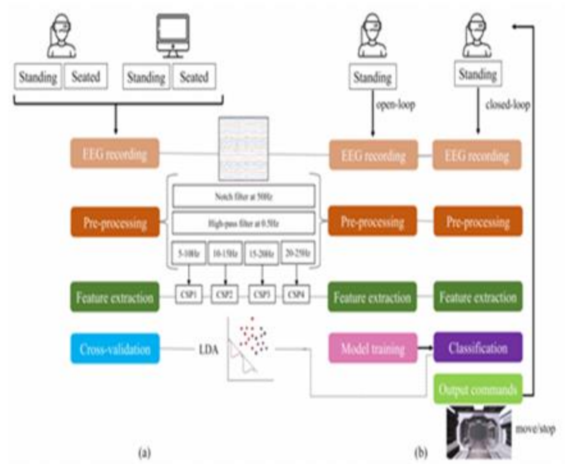
Thus the positional control characteristics of eletro-hydraulic servo mechanism for different input signal were obtained.

The control system using bioelectrical signal and remote wireless communication network was constructed and practically applied in hydraulic positioning systems.

Improving motor imagery of gait on a brain-computer interface by means of virtual reality: A case of study

Motor imagery (MI) is one of the most common paradigms used in brain-computer interfaces (BCIs). This mental process is defined as the imagination of movement without any motion. In some lower-limb exoskeletons controlled by BCIs, users have to perform MI continuously in order to move the exoskeleton. This makes it difficult to design a closed-loop control BCI, as it cannot be assured that the analyzed activity is not related to motion instead of imagery. However the MI performance is affected by several conditions. First, it requires a high focus of the subject during the training of the BCI to adjust the classifier. Any distraction by the subject can easily spoil the data affecting the quality of the classifier model. Therefore, a high control of the experimental conditions is needed, avoiding any external noise or motions. On the other hand, when MI is applied to event related de-synchronization (ERD/ERS).

The paper is organized in two experiments. In both, FBCSP was employed for pattern decoding. First experiment explored the use of an immersive VR environment in comparison to a screen interface. In order to take into account balance issues during MI, both experiments were repeated while the subject was seated and standing up. This first step of the research assessed the accuracy of the proposed BCI as the index to compare the performance of the different interfaces. The second part of the research presented a case of study for the closed-loop control of the VR environment by means of the BCI. Two different experiments were conducted in which users had to perform MI of gait. The objective was to investigate if it is possible to differentiate between periods of MI and resting state while subjects get only visual feedback. In the first experiment, different approaches for the visual feedback were compared and the performances were calculated offline. In the second experiment, the approach that showed the highest performance in experiment 1 was employed for closed loop online sessions. For both experiments, EEG signals were recorded at a sampling frequency of 500Hz. In experiment 1, data were analyzed offline following a pseudo-online approach, whereas all the analysis was done online in experiment 2. From each trial, epochs of 1s with 0.5s of shifting were extracted and processed.



Experimental design. In experiment 1 (a), 4 approaches of BCI with visual feedback were tested offline and results were compared. In experiment (b), subjects first performed trials in which the visual feedback was predefined and these trials were employed to train the BCI classifier. Afterwards, subjects performed closed-loop trials in which the visual feedback changed based on the output of the BCI classifier previously trained. First, data was recorded. Then, it was pre-processed with different frequency filters and common spatial patterns were extracted from each frequency band. Finally, the algorithm performed a classification in two events: MI or relax.

A possible solution would be the employment of virtual reality (VR). During VR training phase, subjects could focus on MI avoiding any distraction. This could help the subject to create a robust model of the BCI classifier that would be used later to control the exoskeleton. This paper analyzes if gait MI can be improved when VR feedback is provided to subjects instead of visual feedback by a screen. Additionally, both types of visual feedback are analyzed while subjects are seated or standing up. From the analysis, visual feedback by VR was related to higher performances in the majority of cases, not being relevant the differences between standing and being seated. The paper also presents a case of study for the closed-loop control of the BCI in a virtual reality environment. Subjects had to perform gait MI or to be in a relaxation state and based on the output of the BCI, the immersive first person view remained static or started to move. Experiments showed an accuracy of issued commands of 91.0 ± 6.7, being a very satisfactory result.

A P300-based brain computer interface for smart home interaction through an ANFIS ensemble

Adaptive neuro fuzzy inference systems (ANFIS) has been applied in brain computer interfaces (BCI) in different ways such as mapping of P300 or fusing information from EEG channels and it has reached high classification accuracy. Adaptive neuro fuzzy inference system (ANFIS) has been used in BCI with considerable results. In, eight subjects are stimulated by an application that shows in a screen one starship to be controlled by P300 occurrence, where an ANFIS classifier is applied to map the P300 signal to a triangle pulse for an easy P300 detection; it got an accuracy of 85%. Fuzzy approach to fuse information from different electrodes to improve the P300 detection, this work reached an score classification greater than 87%. Furthermore, ANFIS classifier was used to control a robot arm by motor imagery, using 4 commands and eleven healthy subjects participated in this experiment. The results reported an accuracy greater than 65% in its classification.

Table I. SUBJECTS GENERAL DATA

Subjects	Age	Handed	Gender	Diagnosis
S1	33	right	Male	Healthy
S2	21	right	Male	Healthy
S3	29	right	Male	Healthy
S4	20	right	Male	Healthy
S5	20	right	Male	Healthy
S6	52	right	Female	Ischemic post-strok
S7	20	left	Male	Hemorrhagic post-str
S8	55	left	Male	Ischemic post-strok

Each subject performs four offline sessions for training. Offline sessions were separated in two per day. Two sessions were separated in breaks of 8 to 10 min. A session has six runs of the program and each run was separated by breaks of 1 min. Participants were informed that they should pay attention and avoid to moving and talking during the EEG recording. The duration of one run and one session (electrodes setup and short breaks) was approximately one minute and 30 min. The images were flashed in random sequences, one image at a time. Each flash of an image lasted 100 ms and after it 300 ms none of the images was flashed (Fig. 3). Each image was intensified more than 20 epochs with a maximum of 25 per run of the program. The mean of EEG signals is calculated, the occurrence and not occurrence of P300 is displayed in Fig. 5; 4-channels (P7, P4, O1, and O2) are chosen due to the observation of P300 and Event-Related Potential (ERP) cortical fucus. Channel selection could change depending on each subject. Healthy subjects S2, S3, and S5 had a similar performance to patients S6 and S8; although patient S7 had the lower performance, this patient has the most critical condition post stroke. The subject S1 presents the best performance of all subjects; but the following best performance belongs to the subject S5, and the subject S8 had a similar performance to the subject S5. It is noticed that patient S7 had the lower performance in average but its best ANFIS Classifier got an accuracy of 80% and F1-score of 80.9%. This performance is lower compared with other subjects yet, but it can be used in a P300- based BCI due to it is greater than 80%. Best ANFIS classifiers will be implemented using Hoffmann approach. In comparison with ANFIS applications to detect P300 waveforms our proposed approach got better results, it achieved accuracies greater than 90% in the most cases.

Table II. CROSSVALIDATION OF ANFIS CLASSIFIERS, ACCURACY AND F1-SCORE BY SESSION

Subj.	Session 1		Session 2		Session 3		Session 5	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
S1	84.0	83.4	92.0	92.2	80.0	81.1	85.9	85.8
S2	77.5	77.4	82.0	81.2	76.0	74.6	74.0	72.5
S3	72.5	72.7	64.0	64.0	78.0	78.7	75.0	74.1
S4	80.0	80.1	83.0	83.2	79.0	78.1	75.0	75.4
S5	77.5	78.1	85.0	84.9	77.5	79.1	78.0	78.1
S6	79.0	78.5	78.0	78.9	70.5	70.7	72.0	71.7
S7	73.5	72.7	68.5	67.9	73.0	72.8	65.5	64.4
S8	78.0	78.7	78.0	76.5	79.5	79.7	78.0	77.5

The results of average accuracy were greater than 75% for all subjects, similar results were gotten for healthy subjects and post-stroke patients, but the better classifiers for each subject have achieved accuracies greater than 80%.

Sensory Integration in Human Movement: A New Brain-Machine Interface Based on Gamma Band and

Attention Level for Controlling a Lower-Limb Exoskeleton

Brain-machine interfaces (BMIs) can improve the control of assistance mobility devices making its use more intuitive and natural. In the case of an exoskeleton, they can also help rehabilitation therapies due to the reinforcement of neuro-plasticity through repetitive motor actions and cognitive engagement of the subject. Therefore, the cognitive implication of the user is a key aspect in BMI applications, and it is important to assure that the mental task correlates with the actual motor action. However, the process of walking is usually an autonomous mental task that requires a minimal conscious effort. Consequently, a brain-machine interface focused on the attention to gait could facilitate sensory integration in individuals with neurological impairment through the analysis of voluntary gait will and its repetitive use. This way the combined use of BMI+exoskeleton turns from assistance to restoration. This paper presents a new brain-machine interface based on the decoding of gamma band activity and attention level during motor imagery mental tasks. This work also shows a case study tested in able-bodied subjects prior to a future clinical study, demonstrating that a BMI based on gamma band and attention-level paradigm allows real-time closed-loop control of a Rex exoskeleton. The exoskeleton used was the Rex (Rex Bionics, New Zealand). The exoskeleton was controlled by wireless communication. The feedback information of the current status of the Rex was acquired by the computer through a wire serial port communication with custom developed software. Rex Exoskeleton has several characteristics which make it different from other lower-limb exoskeletons. First, it is a selfstanding exoskeleton that does not require any crutches and that allows a full standing walking without any vertical inclination. In addition, its walking pattern is very peculiar and far from the anthropomorphic usual gait. The choice of this exoskeleton was made based on the movement limitations it provides. In a Rex exoskeleton, the limbs of the subject are tightly attached to the robotic prosthesis by several straps, avoiding any lower limb movement. This way, the subject can only move their legs when the exoskeleton does, avoiding any lower-limb movement not commanded by the BMI.

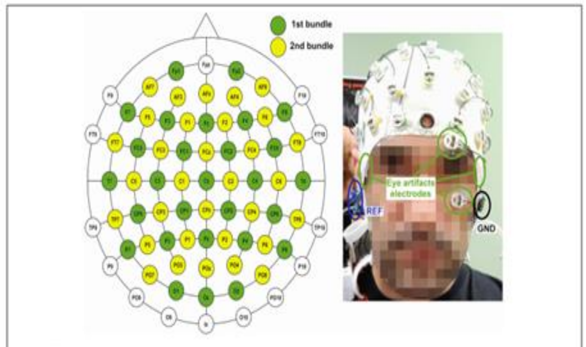
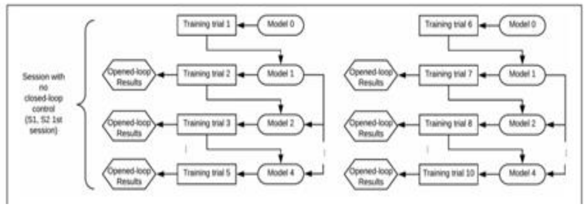
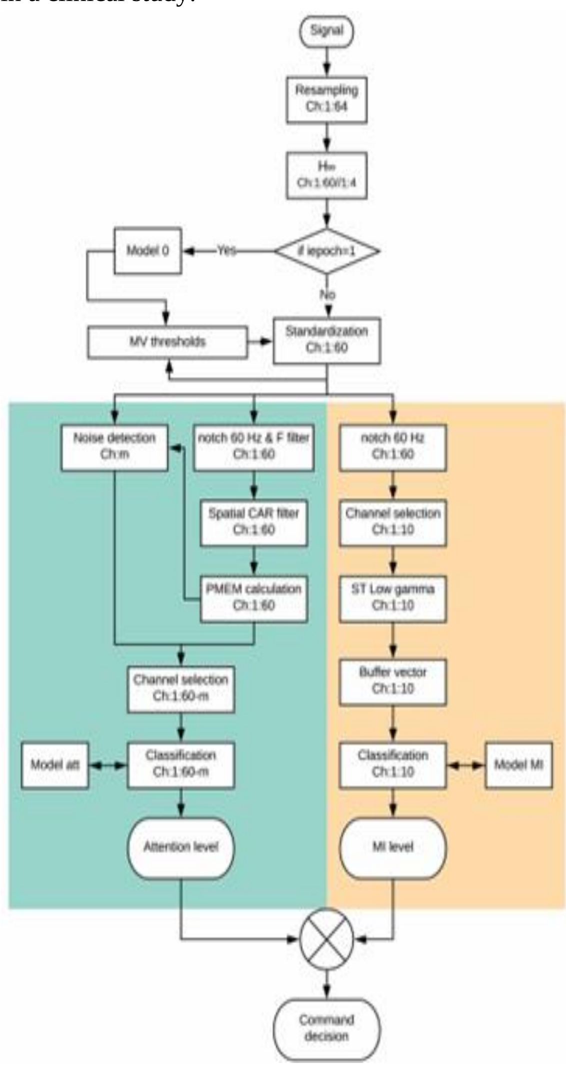


FIGURE 1 | Electrode configuration for the experiments. Sixty of the electrodes were used for EEG recording. Four of the electrodes of the first bundle were used for assessing eye artifacts. Ground and reference were positioned on left and right ear, respectively.



Preparation of the subject included two different steps. First the limb length of the exoskeleton was adjusted to the subject. After that, the electrodes were gelled to a value lower than 30k. Electrode's impedance was checked before starting the trials and after finishing to be sure no electrodes were marginally over the 30k• value. Full process for both tasks could take around an hour. Before starting data collection, a medical mesh was positioned over the cap to avoid any wire movement and mitigate motion artifacts. Before starting, several runs of walking by manual control were accomplished in order to get the subject used to the Rex movement. False Positives (FP) and False Positives per Minute (FP/min) this is one of the most important indices, as it quantifies the number of walking commands issued during rest or count periods. One of the objectives of the research is to kept this number as low as possible, even if it limits the accuracy of the BMI. For the real-time control of an exoskeleton, it is an important problem if the exoskeleton is activated when it is not desired, as it could be frustrating for the patient during therapies or make the control unusable for assistance, all the trials (training and test) were processed in a real-time (online) scenario. Training trials were executed in opened-loop control while test trials were executed in closed-loop control. Each trial was performed following a determined method of control (MI or MI+att). In the case of closed-loop control tests, the method of control corresponds to the one used when registered. However, in the case of training trials, they were simulated again using a pseudo-online analysis. For this reason, training trials show the results of both methods of control and test trials only the method that was actually executed in real time. The experimental sessions fulfilled, show a case of study for the validation of the proposal, which has been validated as a promising technique to operate an exoskeleton in rehabilitation therapies which imply the cognitive engagement of the subject. Future research, will explore how the expertise of the subject can affect both paradigms during several sessions. In addition, the flaws detected in the current proposal will be corrected in future implementations of the BMI, such as limiting the fatigue of the subject with shorter sessions and assuring that the model training trials are not inducing errors in the classifier. All of this, in order to allow its future implementation with non able-bodied subjects in a clinical study.



Scheme of the full processing of an epoch since it is acquired and an output command decision is interpreted. The processing is carried out in the same way for the pseudo and the online analysis in real time. The only difference is that during pseudo-online analysis the command decision is not sent to the exoskeleton. Attention paradigm part is in green while MI paradigm is in beige.

Real-Time EEG-EMG Human-Machine Interface Based Control System for Lower-Limb Exoskeleton

This article presents a rehabilitation technique based on a lower-limb exoskeleton integrated with a human–machine interface (HMI). HMI is used to record and process multimodal signals collected using a foot motor imagery (MI)-based brain–machine interface (BMI) and multichannel electromyography (EMG) signals recorded from leg muscles. Current solutions of HMI-equipped rehabilitation assistive technologies tested under laboratory conditions demonstrated a great deal of success, but faced several difficulties caused by the limited accuracy of detecting MI electroencephalography (EEG) and the reliability of online control when executing a movement by patients dressed in an exoskeleton. In the case of lowerlimb representation, there is still the problem of reliably distinguishing leg movement intentions and differentiating them in BMI systems. Targeting the design of a rehabilitation technique replicating the natural mode of motor control in exoskeleton walking patients, we have shown how the combined use of multimodal signals can improve the accuracy, performance, and reliability of HMI. The experiment, which led to development of the technique, was conducted in eight healthy subjects. The results showed a high accuracy rate in motion intention and execution classification tasks for the EEG and EMG modalities of our mHMI, respectively. Data analysis showed that the combination of EEG and EMG modalities can (i) improve the reliability of movement prediction by decreasing the false positive rate and (ii) enhance the positive detection rate of EEG-based classifications.

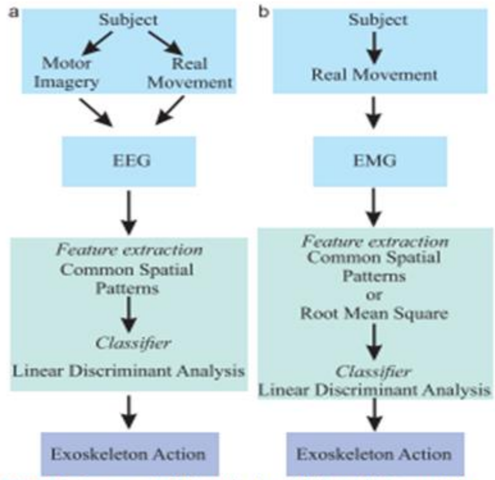


FIGURE 1. Components of the online lower-limb exoskeleton control system: (a) EEG-based HMI and (b) EMG-based HMI.

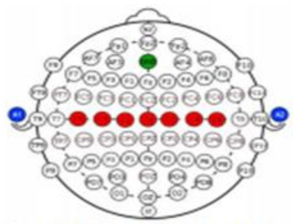


FIGURE 2. EEG electrode distribution in the 10–10 system.

The signal recording module recorded the EEG signal during the MI by subjects and EMG signals during the leg movements. Furthermore, the EEG and EMG data were sent to the processing and classification module, where raw data were preprocessed by a feature extraction procedure. The classifier analyzed the preprocessed data to recognize motion intention. After motion intention is predicted, the control system sends the corresponding command to the exoskeleton, which finally executes the target movement. The scheme of our mHMIbased exoskeleton control system. Disposable gel electrodes were attached to the wires of the NVX 52 amplifier. Two electrodes with one common reference for all channels were used for each EMG channel. Four EMG channels, which recorded the EMG of the musculus tensor fasciae latae (MTFL), musculus rectus femoris (MRF), musculus biceps femoris (MBF), and musculus gastrocnemius (MG), were used for each leg, the location of the EMG electrodes on the leg. Electrode placement on the muscles, their alignment in accordance with fiber direction, and the distance between them were set according to the recommendations of the SENIAM project (surface EMG for the noninvasive assessment of muscles project). Unlike the case of detecting foot MI, we can predict the attempt of real foot movement using combinations of the EEG and EMG signals. We developed two protocols for combining EEG and EMG: (i) HMI based on extracting CSP features with subsequent LDA classification and (ii) HMI based on separate feature extraction and classification, the results of which were combined by logical operators ‘‘AND’’ and ‘‘OR’’ . Here we used EEG- and EMG-based classification for two classes (1: foot movement execution without discriminating between the left or right side; 2: rest because of the low EEG-based classification accuracy value for three classes. The developed system can analyze up to 15 signals simultaneously in real-time during a movement. Foot MI is extracted from EEG signals (seven channels) using the event-related (de)synchronization effect. Supplemented by EMG signals reflecting motor intention, the control system can initiate and differentiate the movement of the right and left legs with a high degree of reliability. The classification and control system permits one to work online when the exoskeleton is executing a movement.

CONCLUSION

Many researchers throughout the world are developing BCI systems that a few years ago were in the realm of science fiction. These systems use different brain signals, recording methods, and signal-processing algorithms. They can operate many different devices, from cursors on computer screens to wheelchairs to robotic arms. A few people with severe disabilities are already using a BCI for basic communication and control in their daily lives. With better signal-acquisition hardware, clear clinical validation, viable dissemination models, and, probably most important, increased reliability, BCIs may become a major new communication and control technology for people with disabilities and possibly for the general population also. BCI technology has already shown promising results in providing assistance in both cognitive and physical support and rehabilitation, and we look forward to future innovation in this important area of research that affects all of us eventually.

REFERENCES

[1] R. S. Vihar, K. S. Priyanka and J. V. M. Lal Jeyan, "Design and analysis for the flutter behaviour of

different selected wing plan forms computationally," 2020 International Conference on Interdisciplinary Cyber Physical Systems (ICPS), 2020, pp. 72-78, doi: 10.1109/ICPS51508.2020.00018.

[2] Ramesh, P.S. and MurugaLalJeyan, J.V. (2021), "Terrain imperatives for Mini unmanned aircraft systems applications", International Journal of Intelligent Unmanned Systems, Vol. ahead-of-print No. ahead-of-print.

[3] Ramesh PS, JV Muruga lal jeyan Mini Unmanned Aerial Systems (UAV) - A Review of the Parameters for Classification of a Mini UAV - International Journal of Aviation, Aeronautics, and Aerospace, Published by Scholarly Commons Embry-Riddle Aeronautical University Volume 7 Issue 3 Article 5 2020

[4] JV MurugaLalJeyan, Kavya S Nair and Krishna S Nair "Aerodynamics and flow pattern performance evaluation of offroad vehicle for various velocity range and angle of incidence" Journal of Physics: Conference Series, volume/ issue 1473 March 2020 012001, IOP Publishing

[5] J V MurugalalJeyan,Krishna S nair , Kavya S nair "The Low Speed Aerodynamic Analysis Of Segmental Wing Profile "International Journal of Mechanical and Production Engineering Research and Development (IJMPERD) ISSN (P): 2249–6890; ISSN (E): 2249–8001 Vol. 9, Issue 4, Aug 2019, 1303–1310