IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 23, Issue 2, Ser.III (Mar. – Apr. 2021), PP 41-45
www.iosrjournals.org

Survey Paper on Various Techniques for Assistive Robotic Exoskeletons

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Abstract: *Many people are suffering from neurological dis- orders such as stroke, central nervous system disorder, and spinal cord injury. The physical demand for both patient and therapist in manual therapy leads to the need for the developmentof robotic exoskeletons for rehabilitation therapy. This paperdescribes the various methods used for building assistive robotic exoskeletons.*

Index Terms: *Exoskeletons, Brain Computer Interface, Electroencephalography, Electromyography*

Date of Submission: 28-04-2021 Date of Acceptance: 12-05-2021

I. Introduction

The advancement of robotics technology has pushed the development of a distinctive field of robotic applications, namely robotic exoskeletons. Robotic exoskeletons have proven effective in providing more intensive patient training, betterquantitative feedback, and improved functional outcomes for patients compared to manual therapy. Mainly the exoskeletons are used for the lower limb therapeutic purpose. The manual rehabilitation is done using a treadmill. One of the drawbacks of using treadmill is that it is not very intensive; the training time is limited to the availability of the personal trainer. Since the gait pattern of the patient is not reproducible, the entire therapy is not optimal. Also, the entire manual rehabilitation training requires great physical effort.

Brain Computer Interface (BCI) technology is a tremendously growing research area having various application. Itsinvolvement in medical field lies with prevention and neuronalrehabilitation for severe injuries. BCI systems try to builda pathway between the human brain and external devices,providing the patients for communication with the world eliminating the scope of depending on others to a less degree. BCIs are often oriented at research, mapping, assisting, augmentingof human cognitive or sensory-motor functions. The growth of BCIs has increased in the recent years, paving way for research and aiming to be more accessible for the people [1]. The BCI technology is classified into two types based on the placement of electrodes- invasive and non-invasive systems.In invasive BCI systems the electrodes are implanted in the brain tissue. Thus, the patient's brain gradually adapts its signals to be sent through the electrodes. The non-invasive systems involve placing the electrodes on the scalp of the patient and taking readings. The non-invasive methods take Electroencephalogram (EEG) readings of the brain. An electroencephalogram is a measure of the brain's voltage fluctuations as detected from scalp electrodes. It is an approximation of the cumulative electrical activity of neurons [2].

The human brain is a complex system, inter-connection of billions of nerve cells (neurons) which exhibits rich spatiotemporal dynamics. The invasive as well as non-invasive techniques for mapping brain signals such as: EEG (Electroencephalogram), (Functional Magnetic Resonance Imaging), MEG (Magneto Encephalography), NIRS (Near-infrared Spectroscopy), PET (Positron Emission Tomography), EROS (Event-related optical signal). The widely used method for examining human brain is EEG which is a non-invasive method. A direct measure of cortical activity with a temporal resolution of less than millisecond is provided with EEG. EEGtechnique can also be used to extract the features of the brain signal even if the subject is not in a state to attend the stimuli.

The first human brain EEG was recorded by Hans Berger in 1929. Previously, its analysis was restricted to visual inspection only. The visual inspection is very subjective and hardly allows any or statistical analysis. The traditional methods are very tedious and several techniques were proposed in orderto quantify the information of the brain signal. The EEG signals are highly non-linear, non-Gaussian, random, non-correlated. The injuries in brain, any such disease or symptom can be detected using Electroencephalography (EEG). It is also used in detecting many diseases related to neurology, such as Seizure disorders like epilepsy, sleep disorders like Narcolepsy, depression and various problems which are related with trauma (stress). The traces are different for different brainactivities. Using signal processing techniques brain activity of a normal and abnormal person can be distinguished easily [3].

II. Literature Survey

A review of the mechanical designs, actuation systems,and control strategies that are currently used in robot exoskeletons for rehabilitation therapy is presented in [4]. The rehabilitation-related robotic exoskeletons are designed to re- habilitate both the lower limbs and the upper extremities. In this paper, emphasis is given to lower extremity rehabilitation. To date there are several types of exoskeletons that have their own advantages during rehabilitation therapy. Here, the discussion is constrained to treadmill-based and over-ground exoskeletons. In addition, a detailed descriptionof the compliance of both the mechanical design and actuation system—pneumatic-based, hydraulic based, and SEA systems—is offered. Moreover, trajectory and intention-based control strategies are given priority in this review.

A lower-body exoskeleton and non-invasive method to mea-sure the brain activity is proposed in [5]. Thus decode a paraplegic subject's motion intention and provide him the abilityof walking with a lower-body exoskeleton. To accomplishhigh decoding accuracies of limb motion parameters, suchas the joint angles and joint velocities, parametric methods such as Kalman Filter, Wiener Filter and soft computing methodologies are used. Here the attention is directed to a shared control architecture, that benefits from the control of definitive parameters of walking by the exoskeleton system. The paper further presents decoding model architecture and the offline decoding results for repeated walking-turning right- turning left motions and sit-rest-stand motions. Also, initial findings on an EEG-based BMI system to control the REX (NeuroRex) exoskeleton in a real-time closed-loop setting, that helps in independent walking for the paraplegic user. With thismethod there is an increase of correct command executions over trials.

The paper [6] studies the use of EEG and electromyogram (EMG) to estimate the upper limb movement intention and control the upper extremity exoskeleton. When the subjects discover that the system is producing an erroneous action, some of the leads in the 256-lead EEG signals carrying the wrong response from the brain. By using the average referenceas a spatial filter to process the EEG signal data and reducing the data volume with a 1 to 10Hz bandpass filter, the channels containing the incorrectly correlated signal or the two leads at the source of the signal are selected to locate the source of error. They find that the accuracy of using EEG-EMG methodsto determine the error is 5% higher than the accuracy of using only EMG.

Witkowski, M et al. [7] proposes a method of using the electrooculography to enhance the BCI to control the armexoskeleton for grasping. The grasping motion of the palmis differentiated by defining the frequency of the sensory-motor rhythm corresponding to the motor image. When the exoskeleton is controlled by motion imaging, the unconscious motion is interrupted by the eye movement signal, therefore the introduction of the electrooculography signal can improve the safety and reliability during the brain-computer interaction.

This paper [8] presents a control approach for a lower limb exoskeleton intended to facilitate recovery of walking in individuals with lower-extremity hemiparesis after stroke. The authors hypothesize that such recovery is facilitated by allowing the patient rather than the exoskeleton to provide movement coordination. As such, an assistive controller that provides walking assistance without dictating the spatiotemporal natureof joint movement is described here. Following a description of the control laws and finite state structure of the controller, the authors present the results of an experimental implementation and preliminary validation of the control approach, in which the control architecture was implemented on a lower limb exoskeleton, and the exoskeleton implemented in an experimental protocol on three subjects with hemiparesis following stroke. In a series of sessions in which each patient usedthe exoskeleton, all patients showed substantial single-session improvements in all measured gait outcomes, presumably asa result of using the assistive controller and exoskeleton.

Salazar-Varas et al. [9] uses BCI to detect sudden obstacles during walking in response to the fact that the alertness of a person would cause brain activity when an accidental disturbance occurs. The experiment is performed on a treadmill and the laser beam is used to simulate obstacles from time to time.Using the slope and polynomial coefficients as features, offline analysis results show that the detection accuracy can reach 79.5% and the best result in the pseudo online experimentis that 11 out of 14 obstacles are detected. The work showsthe feasibility of detecting obstacles in walking through BCI system.

Hortal et al. [10] develops a BCI based on desynchronization (ERD) and event-related synchronization (ERS) phenomena and proposes the start and stop detection of gait cycle based on EEG signals. The experimental results of 4 healthy subjects and 3 patients show that the identified true positive rates are 54.8% and 56.1% respectively. In the real-time test, the average delay for detecting motion intention is 798ms. The article shows that the motion intention in walking can be detected through BCI.

Aiming at the patients with lower extremity disabilities, Jose Luis et al. [11] uses the eigen matrix dimension reduction technique, namely Local Fisher Discriminant Analysis, to process the amplitude-modulated information data collected from the brain signals under specific tasks (sit, stand, turnleft, turn right, etc.). By using the Gaussian mixture model classifier to map the exoskeleton state to the eigen matrix to achieve decoded brainwave under specific tasks, the offline cross validation results show that the classification accuracy can reach 97.74 +- 1.2%.

In this paper [12], bio-signals are incorporated with gait rehabilitation such as electromyography (EMG) or electroencephalography (EEG) for facilitating neuroplasticity. The stroke patients' gait intention are decoded through a wireless EEG system. To overcome patient-specific EEG patterns due to impaired cerebral cortices, common spatial patterns (CSP) was employed. The paper demonstrates that CSP filter canbe used to maximize the EEG signal variance-ratio of gait and standing conditions. Finally, linear discriminant analysis(LDA) classification was conducted, whereby the averageaccuracy of 73.2% and the average delay of 0.13 s were achieved for 3 chronic stroke patients. Additionally, it found out that the inverse CSP matrix topography of stroke patients' EEG showed good agreement with the patients' paretic side. The paper [13] presents a powered exoskeleton called WalkON Suit which is able to do six challenging tasks thatrequired a pilot with complete paraplegia to walk on a level floor, uphill, downhill, and on stairs; stand up and sit down; step on stones; and even pass through a tilted path. The WalkON Suit system consists of a pair of actuation systems, a pair of robotic legs, a backpack that includes a controlunit, circuits, and batteries; a pair of crutches; and a userdisplay. It won the Bronze medal in the Cybathlon 2016.The factors that made the Suit unique and powerful are thespecial technologies, such as a hybrid actuation mechanism, a biarticular transmission system, distributed batteries, anddistributed actuators. The drawbacks of this suit is that it is slower than ReWalk.

The paper [14] aims to investigate the changes of cortical involvement in human treadmill walking with and without BCI control of a walking avatar. The source localization revealed significant differences in cortical network activity between walking with and without closed-loop BCI control. The results showed sustained suppression in the Posterior Parietal Cortex and Inferior Parietal Lobe, indicating increases of cortical involvement during walking with BCI control. The significant increased activity of the Anterior Cingulate Cortex (ACC) in the low frequency band suggesting the presence of a cortical network involved in error monitoring and motor learning is observed. Additionally, the presence of low γ modulations in the ACC and Superior Temporal Gyrus may associate with increases of voluntary control of human gait. This work isa further step toward the development of a novel trainingparadigm for improving the efficacy of rehabilitation in a top- down approach.

The studies containing BMIs for commanding lower-limb robotic systems is reviewed in [15]. The devices, user population, input and output of the BMIs and the robots, neural features, decoders, and system performance were summarized across the identified studies. The tasks often involved classification of discrete state commands such as walking, stopping, and turning. It was observed in the paper that few EEG denoising techniques were implemented or they were not sufficiently validated. Various neural features and decoderswere used for neural classification. Horizontal comparison wasattempted by examining ITR and control efficiency. Overall, the system performance is promising, but far from practical applications because of the small sample pool, potential safetyrisks, and other challenges.

The paper [16] aims to attain a model from which exoskeleton can receive proper instructions by feeding raw EEG signals, so that the robot can help people to step over obstacles.The CSP algorithm is used to extract the features from EEG signals and SVM classifiers are trained to produce spanning commands to control exoskeleton. The average accuracy ofall classifiers can reach 93.14% with a standard deviation of 2.70%.

X. Long et al. [17] uses a heuristic channel selection optimization algorithm with the L1 norm is applied to the BCIsystem. The feasibility of the universal optimal brain electrodechannel subset for an EEG-based lower limb exoskeleton system in the scenario of dynamic motion paradigm is explored and verified. According to the correlation of channelsof four subjects, a universal optimal subset is found and tested on another two new subjects. By analyzing the results,it is concluded that the universal optimal subset can reduce system configuration time without losing excessive systemperformance.

The paper [18] proposes spatio-spectral CNN model having83.4% accuracy on gait state recognition. They achieved gait and stand intention recognition accuracy of 77.3% and 77.7%, respectively. Instead of focusing on specific neural features, thefocus was on the general EEG features which make the study applicable to other EEG studies. They were able to decodegait intention of sub acute or chronic stroke patients as well as healthy subjects. The stroke patient's gait intention recognition would lead to responsive exoskeleton and enhance their gait rehabilitation.

Z. Li et al. [19] proposes a control system based on hybrid EEG/EMG signals for a powered exoskeleton robot to realize going up and down stairs, which utilizes two different motor imagery tasks and the strength of EMG signals to produce different commands. The stair-climbing gait is designed in task space satisfying the environmental constraint and kinematic constraint. Then, each joint angle trajectory in joint space can be obtained by solving the inverse kinematics equation and tracked through the joint feedback controller. The validity andfeasibility of the developed system have been confirmed by climbing up and down stairs with three different volunteers.

The paper [20] presents a new approach for EEG classification. The paper introduces attention-based transfer learning to the EEG classification. The primary method concentrateson the functional areas of the brain where new activities occur. The method consist of a cross-domain encoder and an attention-based decoder. Cross domain encoder contains CNN to extract general features of the images and an adversarial network is applied to train a far better general feature extractor.The output of the cross-domain encoder is fed as input to the attention-based decoder to produce the final EEG label and attention map of the brain. Thus increases the accuracy for EEG systems since it considers only functional units. The attention mechanism automatically identifies the functionalareas of the brain during new activities without any medical expert.

III. Conclusion

The paper first studies the need for robotics exoskeleton for rehabilitation therapy and then the combination of exoskeletonwith brain computer interface using non-invasive BCI systems.The literature review contains the various methods in which the accuracy of exoskeletons using EEG can be increased and also reviews about various hybrid EEG/EMG signal powered exoskeletons. The method proposed by C.Tan et al. improve the accuracy of the EEG classification thereby taking advantage of the medical fact that different brain functional areas play different roles in activities. Thus approach is superior to other state-of-the-art approaches. This approach can be used toautomatically discover brain functional areas associated with activities, which is very useful when dealing with EEG data related to a new activity.

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Ruksana Jalaludeen, et. al. "Survey Paper on Various Techniques for Assistive Robotic Exoskeletons." *IOSR Journal of Computer Engineering (IOSR-JCE),* 23(2), 2021, pp. 41-45.