Electroencephalograph Based Control and Feature Extraction Algorithms for Automated Powered Exoskeleton

Shivam Gupta, Nersisson Ruban, Shivam Kumar

Abstract: Mobility and the posture are the major concern for people suffering from endo skeleton disorders. For such people, exoskeleton provides great support and protection. Mostly Exoskeletons are used for the rehabilitation purposes and can improve the life of an individual who has lost his body part and thus help in assistance. In this article, various technologies which are mainly used for the implementation and performance of exoskeleton are reviewed. The systems are compared based on their accuracy and work reliability. The work discusses the machine used, the movement for which the system is tested, the training algorithms used by different researchers, the input control for the system, controlling element for the system, and their advantages. Various training algorithms are also discussed based on the feature extraction techniques which are used to obtain features from the pre-processed brain signals such as EEG, iEEG, EMG. Applying these features in the training model and robot system and testing of the system in real time or pre obtained data. This research paper is written with the intention to differentiate various techniques used and to analyse the best possible technique for conducting the biomechanical operations processes on the robot and to get the user with the most accurate and reliable system which can be used in daily life. These exoskeletons have their application in the field of medicine , military and even help firefighters for various purposes.

Keywords : Exoskeleton, Electro Encephalo Graph, Brain Computer Interface, Automation, Machine Learning.

I. INTRODUCTION

A powered exoskeleton is a portable wearable device consisting of motors, levers and other parts which reproduces the limb movement with greater endurance and strength. Exoskeletons find major application in rehabilitation engineering for those who lost or doesn't have limbs. This is done using the technique of Brain Computer Interface (BCI) which is the communication between the brain and the external devices either using wires or wireless signals. For non-invasive BCI method, electroencephalography (EEG) is most used because of its ease of use and low cost as the signals are collected from the surface or from the scalp. The Vanderbilt limb exoskeleton system is shown in Fig.1 and

Fig.2 shows the flow chart of the prosthetic limb control mechanism.

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Fig.1 Vanderbilt limb exoskeleton [23]

A. Modules of Exoskeleton system

Control Inputs

The control input signal for Exoskeleton systems is mostly EEG (electroencephalo graphy) while few systems use iEEG (Itracranial electroencephalography) and EMG (Electromyography). But the purpose for both EEG and iEEG are same, they differ in their implementation and on the quality of output. EEG is non-invasive technique and usually the electrodes run across the scalp whereas the iEEG is invasive technique but gives recording which are less noisy.

In EMG, the electrical signals from the muscle activity are recorded using the electrodes which are directly in contact with the skin below which is the muscle [20]. These signals are used as the controlling input in the models or techniques discussed in this review article.

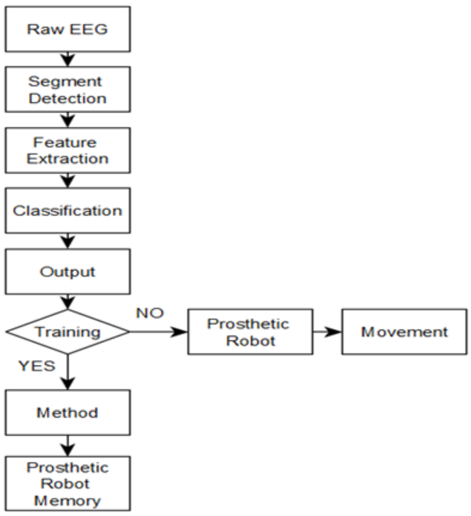

Fig. 2 Flow diagram of the Limb control and machine learning algorithm

Feature Extraction

Feature extraction is the process of reducing the overall dimensionality of pre-processed signal and to gain some useful information from the signals collected like power, energy. Various classifiers for signal processing are studied in this paper. It is although important to keep in mind that the performance of classifier depends upon the quality of pre-processed signal [21]. Shedeed HA et al have discussed about the output or success of various feature extraction[3], the robotic arm was trained using Back Propagation Network, and the classification rate of various techniques were recorded. From the results we found out, Wavelet Transform is the best classifier for the feature extraction of the three compared, whereas Enrique Hortal et al[4], compared few classifiers on the basis of the success in doing five different tasks and the results were the average of the success rate of all the five tasks, which shows Welch's as the best feature extraction classifier. Welch's feature extraction is a non- parametric estimate of the logarithm of power spectral density and Wavelet Transfer (WT) can be used to make it more precise. This use of WT leads to a reduced variance in the power spectral density of noise [20]. Petr Sysel et al have discussed more information regarding the advantages of WT over Welch's feature extraction[20].

Training Algorithms

In this paper, various techniques have been discussed for the movement of the exoskeleton, which can be further worked on to make a complete exoskeleton. Rodolphe Héliot et al[1] discusses the possibility of integrating mechanical impedance to make a more practical system, David P. McMullen et al[2] shows the use of supervisory control to allowing user to work on goal oriented tasks as shown in Fig.5. Shiyuan Qiu et al [5] discusses the use of Lyapunovs fuzzy controller to reduce the training data for the system which is shown in Fig. 3, Hassan Samadi et al[7] shows the possibility of controlling a single robot using multiple users which is shown in the Fig. 4, Eric AP et al [8] shows the ways to improve controllability of the actor over the robot, Guy Hotson et al[10] shows increased autonomy for the subject. Luca Tonin et al[13] also discusses the benefits of the shared-control of a robot. The usage of different cortical activities are given by Andrea Finke et al[14], where the increment in number of control dimensions are reported. Schröer, S. et al[17] shows the advantages of using dry electrodes, and the experiment showing the better detection of 3D positions of the object.

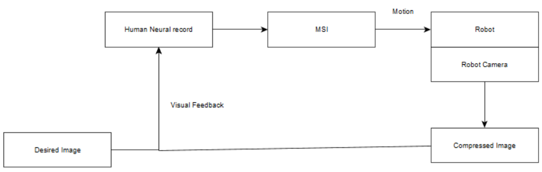

Fig. 3 Flow diagram of fuzzy controller to reduce the training data for the feedback system[5]

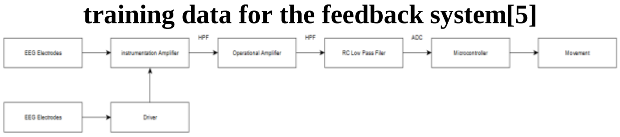

Fig. 4 Flow diagram of controlling a single robot using multiple users control[7]

Algorithms for Autonomy of Exoskeleton

[2], [10], [13] and [17] elaborates the autonomy of the exoskeleton system. They use Burg's algorithm, Recursive Bayesian Estimation, Asynchronous Approach and random trees (RRTs) respectively as the training method for the system. David P. McMullen et al [2], the spectral power of the iEEG signal was computed using the Burg algorithm with a sixteenth order autoregressive model. In Guy Hotson et al[10], the Kalman filter is used which is a repeating Bayesian method for alternating between finding the continuously valued state of a series, and changing the prediction with a noisy measurement of the true value. In Luca Tonin et al[13], asynchronous spontaneous technology is applied; the mental commands are delivered without any external stimulation at any instant of time. In Schröer, S. et al[17], the RRTs are designed to handle non holonomic constrains and can be used for the system with many DOFs shown in Fig.6.

Burg method is an Autoregressive method which is a stochastic process used in calculations in which future values are estimated based on a weighted sum of past values. And the Kalman filter predicts a new state from its previous estimation by adding a correction term proportional to the predicted error which results in minimisation of error [21]. Paths obtained for the robot movement using RRT can be non-smooth. Smoothing technique leads to the creation of short cuts and so to smooth the path, Kalman filter is used[22].

Rodolphe Héliot et al[1], Weiner filter is used to include the environmental or mechanical factors into the algorithm so as to get better implementation of the system in the practical world. Eric AP et al[8], used reinforcement learning to train the robotic arm, in this method a 3-layer feedforward neural network is combined with a Hebbian structure. Andrea Finke et al[14], exploited two different cortical signals using P300 and the Even Related Desynchronization (ERD), this provides distinct dimensions for the robot control that is it helps in changing DOFs of the system.

Reinforcement learning is better than normal neural technique and can use simple signals for training to update algorithms that can be used for more complicated tasks that has many degrees of freedom.

The use of either reinforcement learning[8] or Even Related Desynchronization[14] can help in involving more DOFs and helps in the better practical implementation of the system[1].

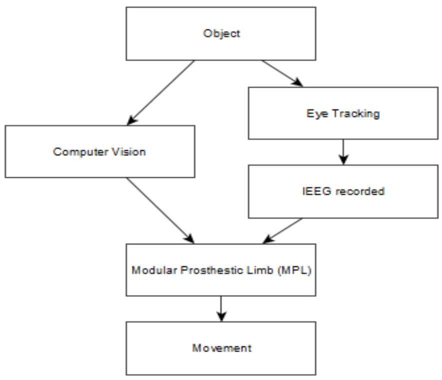

Fig. 5 Flow diagram of Burg algorithm with a 16th order autoregressive model [2]

Weighing Support System

Jun-ichiro Furukawa et al[16], used the Hill-Streve model for designing a system in which, the robot provides only required support after the subject has used his muscle stress in the movement. In this system, the subject is not made to fully rely on the robot, but the robot helps the person to increase the strength and to cure from any muscle damage. Hassan Samadi et al[7], using the fuzzy logic technique, a robot is made to be controlled by various users at a same time. The system takes the brain signals from all the users and using those signals decides which direction to take to move as shown in figure 5. This system is of much use in semi-autonomous cars where if the driver which is controlling car sleeps, the other users present in the car can control the movement of the car.

II. COMPARISON OF VARIOUS APPROCAHES

The various techniques used in different stages of exoskeleton implementation are compared in different parameters. The merits and demerits, advantages of each technique are given in Table I.

A. Training Methods:

Table 1 tells about different approaches in training. 17 various training algorithms are compared based on Movement, training, control input, control method and feedback. The different systems used by number of research group are taken into consideration for this comparative analysis.

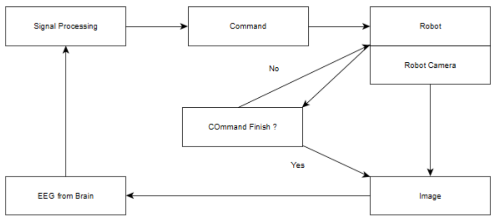

Fig. 6 Flow diagram for detection of 3D positions of the object[17]

III. DISCUSSION

Various papers discussed in the review focuses on arm movement, but the technique used can be integrated to make a whole exoskeleton based on single technique discussed above, the blank column for the feedback states that the data used for testing was taken before and that the testing was not done using real time data, rest of the table is self-explanatory, adding to it, the advantages of various important techniques used above,

In [1], a new control architecture is used to achieve real world application that is to control mechanical impedances (stiffness, intended inertia, damping) to get proper interaction with environment.

In [2], the use of supervisory control allows user to concentrate on goal oriented mechanism and makes the robot to autonomously take care of low level DOF. The HARMONIE system was checked with two subjects. It took 71.4% and 67.7% to perform complex motor task in the subjects and the median of iEEG movement delays were 273 ms and 200 ms.

In [5], the system requirement of dynamic knowledge is very less due to the implementation of Lyapunovs synthesis which is a fuzzy controller. From the results, it is seen that real trajectories nearly coincided with the expected trajectories an optimization program to fit a smooth trajectory based on the EEG signals of the subject, with small error subject 1 had average recognition accuracy of about 72%, subject 2 had 86% and subject 3 had 82%. It is compared with other similar approaches and shown in the Fig. 7.

In [7], in this research paper, instead of controlling a robot from one user, the robot is controlled from multiple subjects. So, when two or more person's selects the same direction, than that direction is correct and the robot takes that direction. The two experiments led to the output response three times faster and the accuracy to choose the correct direction between three subjects using fuzzy logic implementation reaches higher and accurate.

In [8], reinforcement learning in actor-critic control is used. The critic's feedback in the neural networks is used to increase the actor's charge over the robot. The algorithm using 5 trials was able to modify its weight for the money to implement the algorithm effectively to control the robot.

Table. I Various training algorithms and the analysis in exoskeleton system

System	**Movement**	**Training**	**Control input**	**Control method**	**Feedback**
Kirman[1]	2 Degree of Freedom (DOF); Elbow and shoulder	Wiener Filter	EMG	use of kinematic and stiffness variables	position, velocity, stiffness, damping and inertia
Harmonie[2]	Upper limb with 17 controllable and 26 articulating DOFs	Burg algorithm	iEEG	Supervisory control allowing control share between human and robot actuator	Visual Feedback
Robotic Arm; [3][4][8][9] [10] & [15]	Arm movement: Opening and closing, Movement in 2-D plane, multiple DOF	Back Propagation Algorithm in multi-layered perceptron neural network, SVM based system, Reinforcement Learning (RL), Operant conditioning with biofeedback (OCB), Recursive Bayesian Estimation, normalized cross correlation between EEG maps is used to differentiate between two mental tasks	EEG & iEEG	Wavelet Transfer (WT), Principal Component Analysis (PCA) and Fast Fourier Transform (FFT) for feature extraction, Periodogram and Welch's feature extraction methods, A trained monkey was made to move the robotic arm to one of the two distinct targets, Dynamic movement primitives to find the transitions in kinematic state in Kalman filtering and The planar robot move a predefined distance to the user defined direction. The control loop continues until the goal is achieved.	Classification rate: WT is 91.1%, FFT is 86.7%, PCA is 85.6% Periodogram is 39.39 ±2% , Welch's is 47.75 ±4%, A Hebbian structure, 3-layer feedforward neural network, visual feedback, brain signal
Exoskeleton[5]	5 DOF exoskeleton	Local Adaptive Fuzzy Control	EEG	Multivariate Synchronization Index (MSI) method based on S-estimator	compressed images in a non-vector space for SSVEPEEG signal
Robot[6]	Epuck robot movement in right, left, forward and backward directions	Multilayer Perceptron Neural Network	EEG	rat controls the robot by pressing the right or left lever	
Robot[7]	movement of single robot by multiple users	Fuzzy Logic Technique	EEG	microcontroller circuit with ADC inputs of adder circuits	
Neuro-prosthetics[11]		Mutual learning is used in machine learning and the probabilistic classifier with evidence accumulation is deployed to decode the exact intentions of the user	EEG	context awareness shapes the closed loop dynamics	perceptual cognitive processes

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Sanggyun Kim et al [12]		assuming user intent by general Markov process	EEG	causal encoder	perceptual feedback
Telepresence Robot [13]	Right, left steering command	Asynchronous Approach	EEG	The probability distribution using the Gaussian classifier	video/audio communication
Honda's Humanoid Research Robot [14]	Whole Body Motion	using two different cortical activity patterns, Event-Related Desynchronization (ERD) and P300, and then using pattern selection algorithm	EEG	Processing of two data each to detect a pattern using two parallel classification pipelines.	visual feedback
Muscle Support System[16]	knee and ankle joint torque	Using the Hill-Streve model a real time model for torque estimation is built	EMG	The converted vertical forces (of knee and ankle joint torque) are utilized as force load for the PAM actuator system	Desired force estimation using EMG
KUKA Omni Rob platform[17]	arm and hands movement; 7 DOF	Random trees (RRTs) to repetitively probe and search the configuration space given a starting and destination configuration of the robot.	EEG	Doing object detection, motion planning, and motion execution using an assistive manipulator autonomously ie shared autonomy	a clear go-signal is required from the user in each step
Wheelchair [18]	substitute for lower limb	Shared Control	EEG	SSVEP and APF and SLAM in autonomous mode	visual stimulation process was designed to elicit the SSVEP
Kinova-Mico[19]	6 DOF	P300 based robot arm and HCII	EEG	HCII to get visual stimulation and allows user to handle the robot arm at the first-person perspective	visual feedback

In [10], the subjects were able to complete even those tasks using environmental sensors which were not possible by neural control alone. The experimental validation shows the increased level in the autonomy in controlling the neuro prosthetic.

In [13], the results obtained show the advantages of shared-control for the brain controlled robots. The experiment shows that all subjects (including those with disabilities) completed complex tasks in similar time and commands to those used in manual control without shared control. So, it reduces subject's cognitive workload and helps the users in keeping attention for longer duration.

In [14], to get more control dimensions, the system uses two different cortical activity patterns. For projection matrices, two for each pipelines were obtained by solving three optimization task on the training data. The state detection of 0.23 was recorded that is 23% of the actions to be happened by state detection errors and not by the user. The actions differ between 91 for the worst performance and 55 for the best. Standard deviation obtained was 12.

In [17], the experiment shows that the robotic system was able to independently find 3D spot of objects and user and so could plan its movements to achieve its tasks autonomously. Also, the usage of dry electrodes provided the constant signal in complete experiment thus making it an alternative to the wider spread wet electrode system.

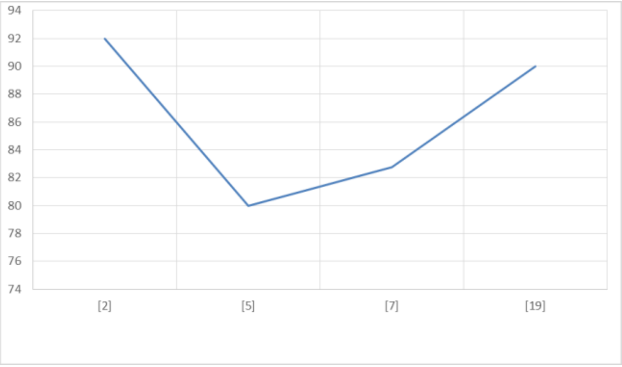

Fig 7. Detection Accuracy among Harmonie[2], Local Adaptive Fuzzy Control[5]and [7], P300 based robot arm and HCII[19]

IV. CONCLUSION

From the section 1.1.2, it is clear that the Wavelet Transfer (WT) method is most suitable for the feature extraction among the discussed papers. The use of mechanical impedance allows the system to be able to get proper environmental interaction. The Lyapunovs synthesis fuzzy controller makes the system less dependent on the dynamic knowledge. Also, the benefits of shared control of the system than the one user controllability show the same rate of completion of task by all subjects including those with disability. Also, to gain the constant signals over the whole experiment, the usage of dry electrodes is recommended.

Section 1.1.4 tells about the different methods to increase the robot autonomy. The usage of random trees (RRT), makes the robot path non smooth and so Kalman filter is applied to make it smoother. The usage of two different cortical signals helps in providing different dimensions and changing DOFs is possible. Reinforcement learning uses simple training signals to refine algorithms which are able to perform tasks involving many DOF

Using the Hill-Streve, model a smart system was made in which exoskeleton just provides with the force only after the person himself has used muscle stress for the movement. This makes the subject not to fully rely on the robot and can help him in restoring his muscle power for the proper movement. These exoskeletons truly enhances the flexibility and allows an individual to work properly .

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