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A survey of Electroencephalogram Based Brain Computer Interface Applications

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Abstract:

This paper presents a review of the application areas that could make use of electroencephalogram based brain computer interface to assist in achieving their tasks and purpose. The scope of work emphasizes medical and engineering applications areas, with a focus on researches in the field of brain controlled robotic systems; principles, classifications, techniques and tasks, in general are discussed, several application examples are summarize. The paper is concluded with a brief of the current and future research directions.

Keywords: Electroencephalogram, Brain Computer Interfaces, Mind commands, Brain actuated robot.

1. INTRODUCTION

The advances in different engineering sciences and in synergetic integration of various interdisciplinary engineering and human fields, as well as, increasing demands in adequate human system integration designs, to increase safety and effectiveness, reduce the system overall complexity, reduce the time needed to perform tasks, simplify training and maintenance, while increasing system capabilities. All of this have allowed the development of advanced reliable and robust machine control, and the ability to acquire electrobiological signals resulted from human's organ or nervous system, extract knowledge from the acquired signals, using this knowledge to determine the human physical or mental state and intention, and finally to transmit different human intentions into machine physical action as a form of appropriate control commands.

Human electrical biosignals can be classified based on acquisition position/organ of human body, as; signals acquired from heart are referred to as Electrocardiogram ECG, signals acquired from muscles Electro-myogram EMG, Electro-oculogram EOG, electrooptigraphy EOG, (eye dipole field) and signals acquired from brain ElectroEncephalogram EEG[1].

Depending on the source of signal recordings, the brain electrobiological signals can be categorized into three categories , *i)* EEG signals, recorded by electrodes on the scalp, *ii)* ECoG signals, recorded from electrode grids on the surface of the brain, and *iii)* single-unit activity, recorded from electrode arrays implanted within the brain. In this article, we are most interested in Electroencephalography biosignals acquired from brain.

By monitoring and recording EEG signals Researchers have succeeded in design of Brain interfaces and brain controlled devices that provide alternative non-muscular channels for communication, entertainment and control. During the last few years, the Brain computer interface BCI, methods for monitoring and recording signals resulted from human's Brain electrical activity using Electroencephalogy EEG, became a very important research topic and have been extensively examined due to novel hands-free mode of interaction with the environment and its applicability in various fields [2].

Electroencephalography EEG, is an electrophysiological monitoring method for measuring the microvolt-sized electrical activity and fluctuations signals of the brain along the scalp, resulting from ionic current flows within the brain neurons [3]. Also EEG can measure the electrical power of the brain by obtaining the power spectral (change the signals from frequency domain to power domain) using Fast Fourier transform. These fluctuations signals are a reflection of the on-going brain dynamics and how the brain functions over time, which present as a series of fluctuations that have characteristic wave forms and amplitude patterns; depending on the cognitive state of the subject [3].The measured electrobiological signals act as a communication between human brain neural system and surrounding environment.

Brain interfaces BI, is a direct communication pathway system between an enhanced or wired brain and an external device, which does not require any external devices or peripheral muscular activity [4]. Brain Computer Interface BCI, uses scalp-recorded electroencephalography[5] to establish direct interaction between the human neural system and machines, aiming to augment human capabilities by enabling people (especially disabled) to communicate, send commands and control devices by mere 'thinking' or expressing intent [6].

Different families of brain interfaces exist, including a mind-machine interface MMI, direct neural interface DNI, or brain–machine interface BMI, and Brain Computer Interface BCI. BCI based technology is a new fast evolving science and research field. It has attracted increasing number of researchers and developers in the development of new generations of BCI systems and to put it in real application.

This paper presents a review of the application areas that could make use of electroencephalogram based brain computer interface to assist in achieving their goal and purpose. It is to help researchers with orientation in EEG application fields and trends. The scope of work emphasizes medical and engineering

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application areas, with a focus on researches in the field of brain controlled robots; classification, design, techniques, and tasks, with some insights into the research and development in this area. We conclude this paper with a brief of the current and future research trends.

The organization of the paper is as follows. In section 2, EEG based BCI basic principles, components and approaches are presented. Section 3 provides a review the EEG based BCI applications areas including classification, control, techniques, and tasks. In section 4, a brief of current, future research directions are presented. In section 5, Discussion and conclusions

2. EEG BASED BCI TECHNOLOGY, BASIC PRINCIPLES, COMPONENTS AND APPROACHES.

A BCI system has an input, output and a signal processing algorithm that maps the inputs to the output [7]. Basically, typical BCI system consists of sequential four basic components; *i)* brain signal acquisition (recording and sending the brain electrical activity waves), *ii)* signal pre-processing, (signal enhancement and noise reduction), *iii)* feature extraction (feature selection, feature extraction and generating the discriminative characteristics), and *vi)* classification (useful features are identified, chosen and classified into logical control signals). The main structure of typical BCI system is shown in "Fig. 1 ".

EEG based BCI data collection, monitoring and recording process is carried out in two ways, *i)* Inpatient, or *ii)* Ambulatory.

In an inpatient method, a special set up is used, a combination of electrode cap, long cables to an amplifier and recording unit, video recording, displays. In an ambulatory method, EEG based equipment are portable, during the recording session, user can move around about their normal daily life.

There are many different companies producing EEG equipment for data collection that vary in reference points or number of electrodes [8]. Some of these companies are Quasar Inc., Emotiv Systems Inc., and Neuro Sky Inc. Neurosky, Uncle Milton, MindGames, Mattel, Microsoft, Hitachi, Sega Toys, IBM, etc. [9].

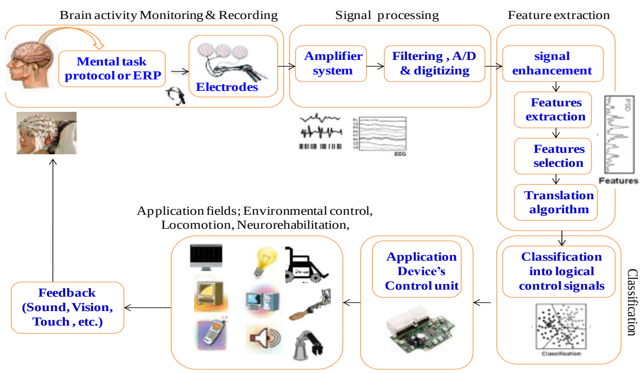

Fig. 1 General structure and working principle of EEG based BCI for controlling devices (e.g. robotic arm or wheelchair) and main components.

2. 1 Brain signal acquisition.

Signal acquisition is the measurement proves of brain signals using a particular sensor modality e.g. scalp or intracranial electrodes for electrophysiologic activity, Functional magnetic resonance imaging fMRI, for metabolic activity [10]. The electrical activity of neurons in the brain produces currents that reach the surface of the scalp, the voltage differences of these scalp potentials are microvolt-sized signals. These signals is detected, monitored and collected using Electrodes.

Electrodes are small, flat metal discs, that are aligned to scalp locations using the standard of 10–20 international system map, at 10% and 20% of a measured distance from reference sites including nasion, inion, left, and right preauricular. A differential amplifier measures the voltage difference between inputs from the active and reference electrodes, (The measured brain electrical activity of each electrode is subtracted from the reference point to obtain information about the brain), with the resulting signal amplified and displayed as a channel of EEG activity [11].

There are two main types of EEG based electrodes; Wet and Dry. Dry electrodes do not require using gel and skin removing or cleaning between electrodes and scalp, this led to increase in contact impedance between electrodes and skin, therefore the acquired EEG signals are worse than those acquired with Wet electrodes. The silver/silver chloride Wet electrodes are most widely applied in scientific research and clinical diagnosis (although other metals such as tin, gold and platinum are also used), reasons for this include their good stability, low cost, low contact impedance because it require removing outer skin layer and filling conductive gel between electrodes and scalp[12].

Number of electrodes and placement-Recordings brain activity may be done with a dense electrode array of 132 electrodes,62 electrode cap, 19 electrodes caps , 16 electrodes as in the consumer-price EPOC Emotiv system, 10 electrode caps , or even as few as one electrode and references as in the consumer-price Neurosky systems [13]. To save time, and labor during setup, many EEG based BCIs use a special electrode cap, in which the electrodes are placed in the right places, according to the international 10-20 system [14]. electrodes are placed at scalp at 10% and 20% points along lines of longitude and latitude of a measured distance from reference sites including nasion, inion, left, and right preauricular.

2. 2 EEG based BCI categorization.

BCI systems can be categorized differently. BCI systems can be classified based on implementation methods for monitoring brain activity as: *i)* invasive, *ii)* partially invasive and *iii)* non-invasive methods. Also BCIs system can be classified as, *i)* independent ,or *ii)* dependent, another BCIs system classification, can be as, *i)* exogenous or endogenous. Based on operating mode, BCIs system can be categorized as, *i)* Synchronous BCIs and, *ii)* asynchronous BCIs. also BCIs system can be classified as *i)* Online BCIs (are one that working in real-time, and makes it possible to provide feedback for the user) and, *ii)* offline BCIs.

In this work we are most interested in BCI categorization based on implementation methods, *i)* invasive, *ii)* partially invasive and *iii)* non-invasive methods, these are shown in "Fig. 2(a) ".

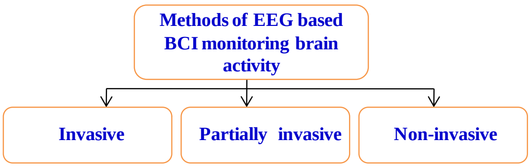

Fig. 2(a): EEG based BCI implementation three methods

Invasive (implanted) BCI system, are the ones that are implanted directly into the brain and acquire the highest quality signals, where the activity of single neurons is recorded from microelectrodes directly implanted in the brain cerebral grey matter.

Invasive BCI systems are mainly used to restore special sensations, such as visual sense, and motor functions for paralyzed patients. However, invasive BCI systems have the disadvantage of easily causing immune reaction and callus, which most likely lead to the regression and disappearance of neural signals. In order to solve these problems, many researchers have focused on noninvasive BCI [1].

In 1980 Schmidt investigated the possibility of making long-term invasive (implanted) BCI connections system to the central nervous system with microelectrodes to control external devices [15]. In the year 2000, Nicolelis had successfully realized an invasive BMI on a night monkey, which reconstructed its arm movements to obtain food by operating a joystick [1]. This open-loop brain machine interface, BMI based system was upgraded to test a closed-loop motor control on a macaque monkey. The monkey was able to control movements of a robot arm to grasp an object by a moving cursor on a video screen via visual feedback [1, 16].

Partially invasive BCI system, are the ones that are implanted inside the skull but dwell outside the brain instead of dwelling within the grey matter. The signal strength using this type of BCI is comparatively little weaker than those of the invasive BCIs [17].

Non-Invasive method is one in which sensors or scanning medical devices are horsed on headbands or caps to read brain signals. When is compared to invasive method, non invasive BCI method has the lowest signal clarity, but it is considered to be easiest, simplest and safest BCI method [17]. Most non-invasive BCI systems use electroencephalogram EEG [18].Noninvasive BCI systems have found a wider application For humans, it is preferable to use non-invasive method, to avoid the risks generated by permanent surgically implanted devices in the brain, and the associated ethical concerns [18].

Non-invasive BCI systems have found a wider application. Early in the 1990s, Niels Birbaurmer had translated the EEG signals of paralyzed patients into control commands to control the cursor of a computer. In the following years, the EEG-based BCI has been largely researched to analyze the characteristics of brain signals from the scalp and apply it to control intelligent devices to assist paralyzed patients with their daily lives[1].

As noted, different families of brain interfaces exist, but two main families exist. Brain-computer interfaces (BCIs) usually refers to BCI that use non-invasive technology. Brain-machine interfaces (BMIs) often refers to implanted brain-interfaces.

2.2.1 Classification of brain activity monitoring BCI technologies.

General classification of currently available brain activity monitoring BCI technologies is shown in "Fig. 2(b)"and include; electroencephalograph, EEG; magnitoencephalograph, MEG; Magnetic Resonance Imaging, MRI, functional Magnetic Resonance Imaging, fMRI; Diffusion Magnetic Resonance Imaging, dMRI; defusion tensor imaging ,DTI; electrocorticography ,ECoG; multiple electrode array MEA.

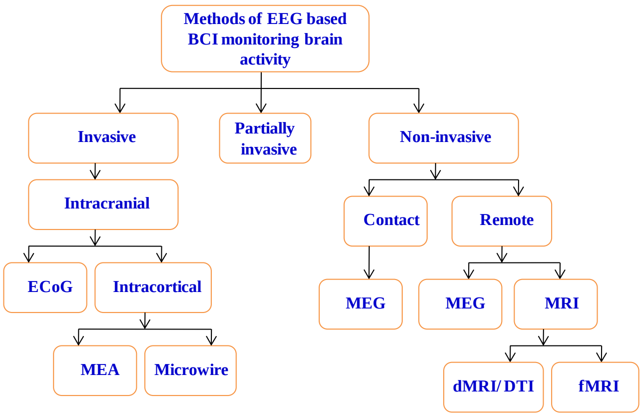

Fig. 2(b): General classification of currently available brain activity monitoring BCI technologies

2. 3 Signal pre-processing

Pre-processing stage include, the amplification of microvolt-sized signals to levels suitable for electronic processing, initial filtering to remove noise and other undesirable signal characteristics, finally analog to digital conversion that is digitizing the analog EEG signal.

Different methods are used to enhancement acquired signal and reduce or remove line or other frequency-specific noise, include, *i)* Filtering, mainly using low-pass filter, high-pass filter, band-pass filter, and notch filtering, *ii)* Computational independent component analysis (ICA), compared with filtering it is difficult to use and with high complex algorithms, *iii)* Wavelet transform.

2. 4 Feature extraction.

Machine learning a field of computer science focuses on the development of computer programs, algorithms, that can access or receive input data and use this data to learn for themselves. Mainly machine learning algorithms can be classified into two modules: signal processing (also known as feature extraction) and classification. In BCI system design, to learn from a training dataset how to classify the signals of a specific user, machine learning algorithms are applied.

In **Feature extraction** stage, from the preprocessed and digitized EEG signal certain features are selected, extracted to generate the discriminative characteristics and representing them in a compact form suitable for translation into output commands. Because much of the relevant brain activity is either transient or oscillatory, the most commonly extracted signal features in current BCI systems are time-triggered EEG or ECoG response amplitudes and latencies, power within specific EEG or electrocorticography ECoG frequency bands, or firing rates of individual cortical neurons [10].

2.4.1 EEG signals features and methods

Various signals can be extracted from the EEG signals to develop BCI systems. BCI systems based on the signal features they use are subdivided in categories. In identifying distinguishing characteristics, the used extraction methods play an important role. The main goal in this stage is not selecting a feature, but to form distinct set of features for each mental task.

BCI systems using EEG signals are subdivided in categories based on the signal features they use. Some of these features are elicited naturally by external stimuli while need to be learned by the user through self-regulation and feedback. Current systems commonly extract one of the following; *i)* steady-state visual evoked potential SSVEP, are signals that are natural brain responses to visual stimulation at specific frequencies approximately 6 and 100Hz, these signals has high accuracy, very low training time and high transfer rates, *ii)* event-related potentials, it is the direct brain response to a specific stimulus /event e.g. sensory, cognitive, or motor event *iii)* Slow cortical potentials SCPs , are slow positive or negative direct current shifts that can last up to several seconds. Voltage changes over 0.5-10.0s. Negative shifts represent cortical activation (e.g. movement) while positive shifts represent reduced activation, *v)* Sensorimotor rhythms SMRs, recorded over sensorimotor cortex at 8–12 Hz (mu rhythm) and 18–26 Hz (beta rhythm), changes occur with sensorimotor stimulation or motor imagery, *vi)* P300 Event Related Potentials [19]. As shown in "Fig. 2(c) ". The P300 and steady-state visual evoked potential SSVEP, are examples of the EEG pattern recognition approach , that are elicited naturally by external stimuli while others like the sensorimotor rhythm SMR, and slow cortical potential SCP, are examples of the operant conditioning approach, that need to be learned by the user through self-regulation and feedback.

P300 Event Related Potentials ; Classical event related potentials ERPs, include several positive and negative waves, such as P1, N1, P2, N2, and P3 (namely, P300, here P for positive, 300 for the 300-millisecond delay) according to the emerging sequences and polarities. The P300 ERP is a positive deflection in the EEG occurring 300 ms after stimulus onset and is a reliable, easy to detect event-related potential. It is an Event Related Potentials that occurs about 300 ms after the user consciously attends to a changing visual stimulus.

The P300 wave, and variation in amplitude and latency; the wave occurs if the user is engaged in the task of detecting the targets. The wave amplitude varies with the improbability of the targets. The wave latency varies with the difficulty of discriminating the target stimulus from the standard stimuli. Typical peak latency when a young adult subject makes a simple discrimination is 300 ms [20]. In 1965, Sutton et al. discovered an electrical potential that exhibited a positive fluctuation within approximately300 ms after the presentation of an unexpected event (visual auditory, etc.) [21] Smith, named this potential "P300" potential based on its polarity and relatively fixed latency [22][1].

2. 5 Classification

In this stage, in the extracted features, useful features are identified, chosen and classified 'translated' into logical control command signals using an algorithm.

Different classifiers are used; nearest neighbor, linear discriminant analysis (LDA), to nonlinear neural networks (NN), support vector machines (SVM), and statistical classifiers [23]. To identify chose and classify useful features, the classifier can be designed to be from from a simple linear model to a complex nonlinear neural network trained to recognize different mental tasks, with the exception of simple threshold detection [24]. The EEG data containing different mental tasks, the classifier is trained to classify EEG online and provide feedback for the user or control device.

The final stag is the device output; here the created logical control commands are used to operate an external device, for example mobile robot or neuroprosthetic.

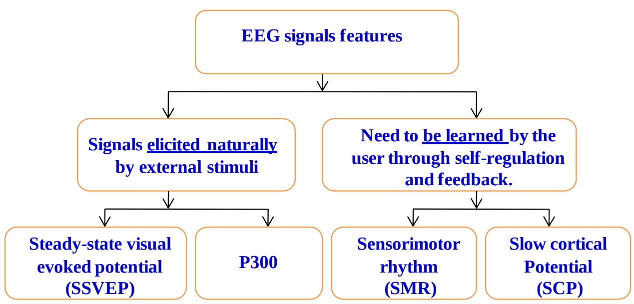

Fig. 2(c) : EEG signal features and classification

2.6 BCI design approaches, EEG paradigms, electrical signal approaches and analysis.

Human brain waves generate different brain rhythms, in response to the human state and level of consciousness. Different human actions and thought affect these rhythms. This fact used as the basis for the BCI. Two fundamental approaches to BCI design shown in "Fig. 3" **,** *i)* the EEG pattern recognition approach based on different cognitive mental tasks. This is based on the fact that, The human brain is functionally organized different brain cortical areas have different functions, therefore different mental tasks should activate different cortical areas and produce detectable and different EEG patterns /rhythms, and *ii)* the operant conditioning approach based on the self-regulation of the EEG response [25],where in a biofeedback environment, by long training sessions, the user is required to gain the skill to self-regulate brain activity.

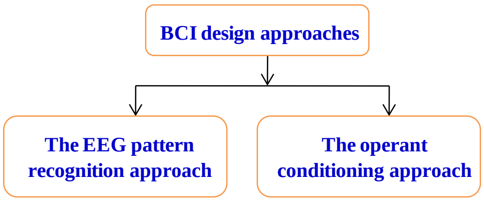

Fig. 3: BCI design approaches.

To control a BCI, users have to acquire conscious control over their brain activity. Three fundamentally different EEG Paradigms approaches that let users control their brain activity and signals. ("Fig. 4"), *i)* Rhythmic brain activity, *ii)* Event-related potentials ERPs and *iii)* Event related desynchronization /synchronization (ERD/ERS).

Rhythmic brain activity-The measured neural oscillations of brain electrical activity and brain waves generated by brain structures are in raw, unfiltered, unprocessed data. The resulted signal is a mixture of several base frequencies, which reflect certain cognitive, affective or attentional states. Because the resulted frequencies vary slightly and are dependent on individual factors, stimulus properties and internal states, (e.g. level of consciousness), these frequencies vary slightly. Research classifies these EEG frequencies based on specific frequency ranges, or frequency bands or rhythms that are named after Greek letters Delta band (1 to 4 Hz), theta band (4 to 8 Hz), alpha band (8 to 12 Hz), beta band (13 to 25 Hz) and gamma band (> 25 Hz).

Event-related potentials, ERPs were originally called evoked potentials (EPs) because they were electrical potentials that were evoked by stimuli**,** is the common title used to describe the potential changes in the EEG signals that occur in response to a particular "event" or a stimulus. It can be further divided into, *i)* steady state evoked potential SSEP, and, *ii)* event-related potential ERP [26][23]. *iii)* Visual evoked potential (VEP).

Steady State Evoked Potentials SSEP, are evoked by a stimulus modulated at a fixed frequency and occur as an increase in EEG activity at the stimulation frequency [27]. Event-related potential ERP, describe the potential changes in the EEG that occur in response to a particular event or a stimulus [28]. It is a time-locked deflection on the ongoing brain activity after exposed to the random occurrence of a desired target event [23]. The event could be a sensory stimulus, a cognitive event, or the execution of a motor response [23]. Visual evoked potential term to describe ERPs elicited by visual stimuli.

Event related desynchronization/synchronization (ERD/ERS) -It has been found that changes caused by some events can block or decrease the power of the ongoing EEG signal. They are time-locked to the event but not phase-locked, and thus cannot be extracted by a simple linear method, such as averaging [23]. To detect these changes, the power variation (decreases or increases) in given frequency bands can be used. This may be related to the synchrony level of the underlying neuronal populations. The power decrease is called event-related desynchronization or ERD while the power increased is called event related synchronization (ERS) [29][23].

Event-related desynchronization (ERD) can be defined as an amplitude attenuation of a certain EEG rhythm. While Event-related synchronization (ERS) is an amplitude enhancement of a certain EEG rhythm [30].

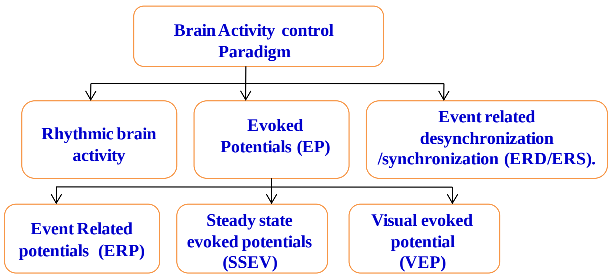

Fig. 4: Approaches to acquire control over brain activity (control Paradigms)

2.7 EEG - Advantages and disadvantage

Advantages - EEG based equipments can be portable, the procedure is a relatively low cost, simple in use, fast, silent safe (without real safety restrictions), does not disturb a subject, and lack of risk. EEG invasive procedure does not cause any pain. EEG offers great temporal resolution or the ability to better understand what time the event occurred in relation to stimuli [30]. EEG based equipments can be designed to be accessible for consumer and non-medical use.

Disadvantage - EEG has limited spatial resolution in comparison to functional Magnetic Resonance Imaging (fMRI) techniques. The electrodes are used to measure brain activities from a particular scalp location, therefore it is not guaranteed that the measurements are originating from the measured areas of the skull. Signals may originate from neighboring areas of the brain and be recorded by other electrodes [8]. Because of the poor signal-to-noise ratio due to the small amplitude of the recorded signals, to extract useful information from EEG, it is required complex data analysis and large numbers of subjects. User may experience discomfort from gels, saline solutions, and/or pastes and electrodes.

3. EEG BASED BCI APPLICATIONS

Since the first time EEG was introduced when electrical signals produced by brain activity recorded by Richard Caton in 1875 from the cortical surface of animals, and from the human scalp by Hans Berger in 1929. The idea of using EEG as means of communication, transferring messages, commands and control to the external world[9], has attracted increasing number of researchers and developers in the development of new generations of BCI technology and to put it in real application, this is see in "Fig. 5(a)". EEG based BCI technology is applied in various fields, including medical, Neuroentertainment, Biometry (security and authentication), Cognitive training (Neurobics), Biofeedback, Neuroergonomics and Neuromarketing and advertisement. These application fields are shown in "Fig. 5(b)".

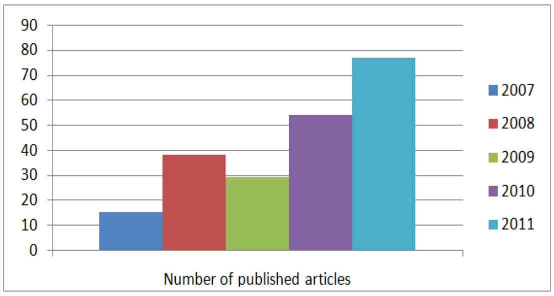

Fig. 5(a): The numbers of EEG based BCI applications developed in BCI articles introduced from 2007 to 2011[82]

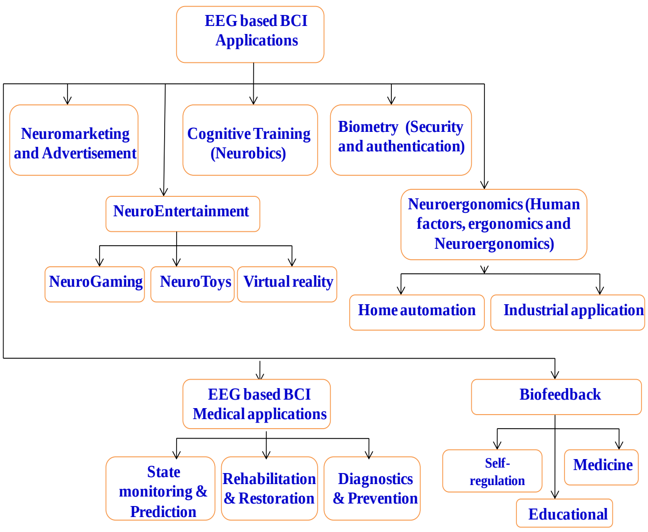

Fig. 5(b): EEG based application fields.

3.1 Medical EEG based applications

The BCI based medical application field has seen rapid growth due to its potentials for offering a new means of control for devices tailored to severely disabled and paralyzed people: examples include directing the motion of a motorized wheelchair, controlling a semi-autonomous assistive robot, and using a neuroprosthesis [31]. As depicted in "Fig. 6", EEG based technology can contribute in the following Medical-clinical applications; state monitoring, prediction and prevention, diagnostics, and rehabilitation.

3.1 State Monitoring and Prevention.

The generated EEG signals varies depending on patient's metabolism and function of their brain, in particular, hypnotic state, presence of pain, dosage of sedative agents, therefore EEG based technology is applied to provide the ability to continuously on-line monitoring and assessment of human's (patient's) state, where, monitoring generated EEG signals, can be an additional source of information to help identify the changes in patient's status. Other examples on EEG based application in human's state prediction and prevention include monitoring heart rate, monitoring the depth of sleep, monitoring patients in a coma, monitor and evaluate the effect of medical treatment, and to monitor the dosage of hypnotic drugs.

Monitoring patients in a coma can give information about an emotional, cognitive or effectiveness state. Monitoring the depth of sleep give information about potential risks associated with sleep disorders.

EEG signals can be used to monitor patients in the intensive care unit ICU, specially patients with neurological deficits e.g. brain trauma or subdural hemorrhage.

Other application examples include, a prediction of motion sickness declines in a person's ability to maintain self-control, resulting in traffic ascendants. A prediction of motion sickness could contribute in a driver-state monitoring and alertness system using a set of EEG power indicators [20]. EEG technology is used to predict and prevent loss of some brain function resulting of smoking and/or alcohol drinking. The use of continuous EEG (cEEG) recording in Intensive Care Units (ICU) can now provide prompt and therapeutically important data regarding cerebral function in a cohort of patients who may have only subtle or no clinical signs [32].

The of negative influences of drugs, smoking and alcohol on brain and resulting loss of some function and decrease of alertness level, can be studied and prevented using EEG signals. In [33] EEG pattern of smokers for theta, alpha and beta band frequencies where studied and analyzed, while in [34] implement a study on human brain after consuming alcohol based on EEG signal.

3 .1.2 Detection and diagnosis

EEG technology is used to early, detect, diagnose and evaluate various health issues including concussion, neurological disorders, (such as epilepsy and narcolepsy), abnormal brain structure (such as brain tumor). EEG tests are used to early detection of Alzheimer's and diagnosis for different dementia subtype.

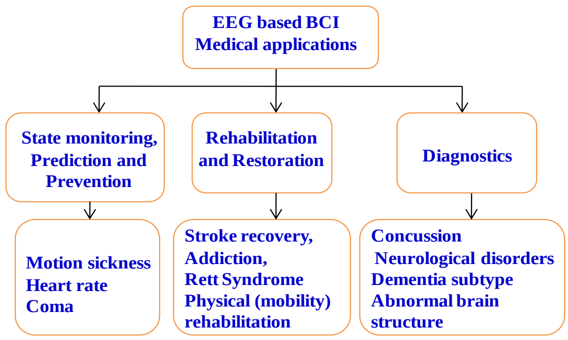

Fig. 6: Medical application fields of EEG based BCI technology.

3.1.3 Rehabilitation and Restoration

EEG based BCI technology is applied in clinical rehabilitation, in two ways; *i)* to substitute for lost neuromuscular function[35] or *ii)* restore motor function by inducing activity-dependent brain plasticity to restore more normal brain function[36].

EEG based BCI Clinical rehabilitation application including stroke recovery, addiction, Rett Syndrome and physical (mobility) rehabilitation. Mobility rehabilitation is a form of physical rehabilitation used with patients who have mobility issues, it is carried out at clinic or home to restore lost functions, improve mobility, or adapt to their acquired disabilities. Several publications provide evidence that the use of motor imagery MI, based BCIs can induce neural plasticity and thus serve as an important tool to enhance motor rehabilitation for different kind of patients [7]. Many rehabilitation protocols work on the premise that repetitive movement practice will restore motor function via crucially activity-dependent brain plasticity ADBP, but rehabilitation must be carefully targeted because ADBP can either lead to restoration of normal function or, if repetitive abnormal movements are made, exacerbate or even establish abnormal function [37].

There are three main BCI-based rehabilitation training approaches, *i)* Real, *ii)* Virtual, and *iii)* Augmented.

In real rehabilitation approach, patients improve their thinking behavior to resemble recorded healthy peoples brain signals retraining healthy areas of the brain to take over. In virtual reality rehabilitation approach, patients retraining brain areas by monitoring and controlling animation movement. In [38] is described how a completely paralyzed patient, diagnosed with severe cerebral palsy, was trained over a period of several months to use an EEG based BCI for verbal communication. In how a completely paralyzed patient, diagnosed with severe cerebral palsy, was trained over a period of several months to use an electroencephalography (EEG)-based brain–computer interface (BCI) for verbal communication. In [39] author design a Brain computer Interface for high-level control of rehabilitation robotic systems, in this system BCI using Steady-State Visual Evoked Potentials (SSVEP) is used as an inputting tool for the human machine interface (HMI) of the semi-autonomous robot FRIEND II.

The BCI unit was used to interpret and translate user's high-level requests into control commands for the FRIEND II system. In the current application, the BCI is used to navigate a menu system and to select commands such as pouring a beverage into a glass.

For rehabilitation training after a stroke. In [40] developed a combined functional electrical stimulation FES-robot system which was continuously driven by the user's residual electromyography on the affected side for wrist joint training after a stroke, in order to involve the user's own neuromuscular effort during the training.

In [41] is proposed a BCI system that is able to control two different feedback devices. The first device is a rehabilitation robot that is used to help in moving the fingers of the effected hand according to the detected MI.The second device applies feedback to the user via virtual reality (VR), here the VR visualizes two hands that the user sees in a first perspective view, which open and close according to the detected MI.For patients who have mobility or communication issues, especially who cannot recover previous levels, BCI based neuroprosthetic devices, can be used to restore or improve normal functionality [42].

3.1.4 EEG-based brain-controlled robotic systems

The word robot is derived from Slavonic word, *Robota*, meaning drudgery. Robots gradually entering different human life fields. Robots are widely used in industry, in engineering application and in medicine. Assistive robots can provide support for disabled people in their daily and professional life.

Elderly, patients who cannot recover previous levels of mobility or communication, people with devastating neuromuscular disorders, who have lost most of their voluntary muscle and speech control, and severely disabled locked-in, are difficult to operate assistive robots with a conventional input device such as a keyboard, a mouse, or a joystick. For this reason, some special interfaces like sip-and-puff systems, single switches, and eye-tracking systems have been proposed [43]. These category of people want, as much as possible, to take control over their life, health, motion, safety improve the quality of life and self-independence. Brain–computer interfaces BCIs, have been developed to address this challenge [44]. In particular design and development of an EEG based brain controlled robot. These systems have been proposed as a new control interface to translate different human intentions into appropriate motion commands for robotic applications.

A brain controlled robot is a robot that uses EEG based BCI as communication and control tool between human brain and physical devices, these systems have been proposed as a new control interface to translate different human intentions (patterns of brain activity) into appropriate motion commands for robotic applications in real time[45].

Brain controlled robots can be classified intro four classes*; i)* brain controlled mobile robots, *ii)* brain controlled manipulators and, *iii)* brain controlled humanoid robots, *vi)* Drone Control, this is shown in "Fig. 7" General structure of EEG based BCI for controlling robots (robotic arm, or wheelchair) is shown in "Fig. 1 " up.

EEG-Based Brain Robot Interaction Systems- In the application of BCI-based cognitive models to control external mechanical devices, such as a robot arm, a wheelchair, or a humanoid robot, Brain Robot Interaction BRI, has become more and more popular. A Brain Robot Interaction BRI, system is a closed-loop control system that uses brain signals in combination with surrounding information feedback. To help in making proper decisions, the robot must provide feedback of the surroundings to the operator. Therefore, an ideal setup for a BRI system usually consists of evoking sources (for SSVEP or ERP) to generate specific brain signals, signal acquisition devices, data analyzing systems, and control objects, among which the signal generating and data analyzing are the most challenging and worthy researching tasks[1].

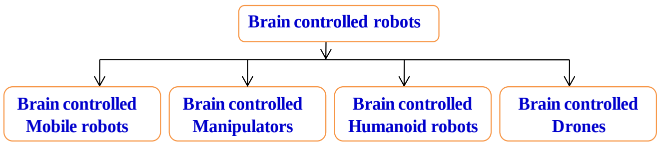

Fig. 7: Classification of Brain controlled robots

3.1.4.1 Brain controlled mobile robots

The development of brain controlled mobile robotic system is very challenging task, reasons for this include, robotic systems are designed to provide support and assistance for disabled people in daily and professional life, steering robotic systems (e.g. a wheelchair) is a complex task, control of robot systems via brainwaves must consider surrounding environment feedback in real-time, robot mechanical kinematics, and dynamics, as well as robot control architecture and behavior [1]. Beside this, Brain controlled mobile robotic systems requires stricter requirements for higher safety, accuracy, reliability and overall performance than for many other applications [46].

In 2004, Millan et al, proposed the first EEG based brain controlled mobile robot [47] .Since then, many research papers have been written in the design and development of various brain controlled mobile robots. "Fig. 8 " shows the number of published papers on brain-controlled mobile robots between 2004 and 2011.further Brain controlled mobile robots are classified according to control type and operational mode, then further classified according to the switching mode [44],

There are three main applied operational mode techniques to implement the control over brain controlled robots, *i)* Direct control by the BCI, *ii)* intelligence technique (intelligent controller) and *iii)* Shared control by the BCI (human) and intelligent controller. This classification and main applied techniques are shown in "Fig. 9 ". In Direct control, users are in direct control over their movements by issuing needed control commands, no needed for additional robot intelligence; therefore the cost and programming complexity are low. But here it is important to consider that EEG-based systems have been considered too slow for controlling rapid and complex sequences of movements [18]. The system overall performance, depends on the performance of BCI system, also user being in direct control by issuing control commands causes user fatigue.

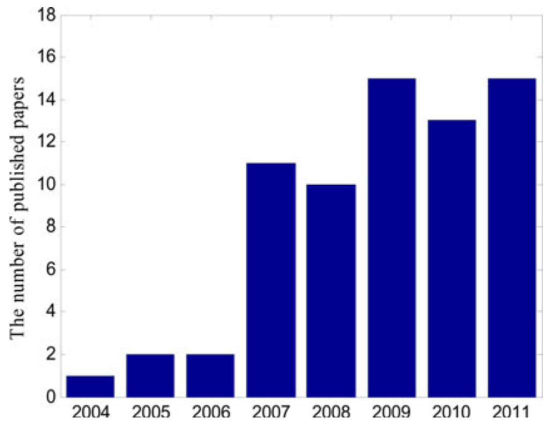

Fig. 8: Number of published papers on brain-controlled mobile robots [44].

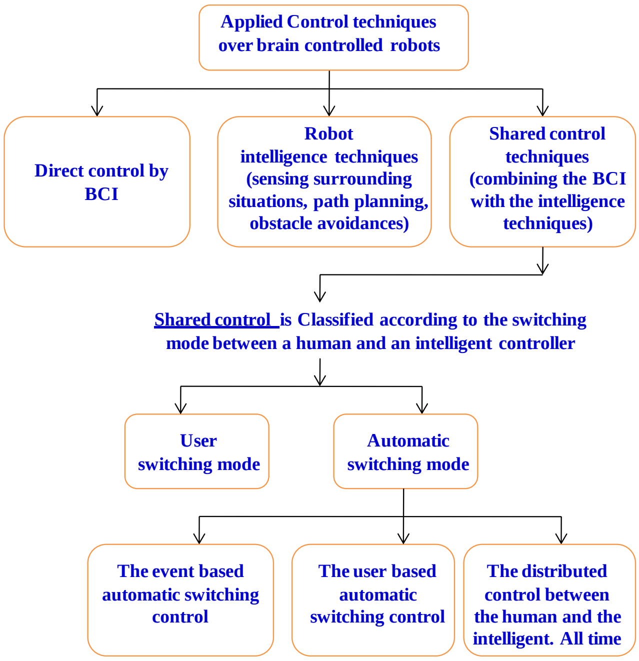

Fig. 9: Classification and main applied techniques to implement the control over brain controlled robots

The second category ; the intelligence technique, where an intelligent controller is used to control all the actions required, for example in sensing surrounding environment and situations, localization, path planning, and obstacle/collision avoidances, such as autonomous navigation system.

The third category, the shared control technique; this term is applied in robotics when both an intelligent control system and a human operator are in control of a given system. Shared control is done by combining the BCI (a human) and intelligent controller to share the control over the robot. It is applied to overcome problems associated with human nature such as dangerous situations, accidents, accuracy and fatigue, the shared control has been widely applied into robotics. The user's safety is better ensured, users being in less direct control, therefore develop less fatigue. Because of the use of sensors and interfaces, the cost and programming complexity are high.

The shared control approach can be, further, classified into two groups according to the switching mode between a human and an intelligent controller; *i)* User switching mode; The user to explicitly switch the control, *ii)* Automatic switching mode; automatic (implicit) switching control between human and an intelligent controller. Because this switching control method is more natural and efficient for disabled people [48]. it has received more research attention in the assistive technology community [44].

The automatic switching control approach can be categorized into the following three classes, *i)* The event based automatic switching control; in this class, most of time, human controls the robot, the intelligent controller is activated/switched in an automatic way, when a predefined event or situation is detected such as an obstacle. *ii)* The user based automatic switching control; in this approach user provides or selects or a mission a target (e.g. a desired location), the automatic control implement it. In this lass user can at any time override the automatic control and take over.

In the first two classes, event and user based automatic switching , at a particular time the robot is controlled by either the human or the intelligent controller, meanwhile in distributed control class. the third class is *iii)* The distributed control between the human and the intelligent controller at all times.

In [47] Direct control by EEG based noninvasive BCI system is applied to control brain controlled robot in the form of wheelchair in real-world situations. In the designed system robot motions are directly controlled by issuing control commands translated from user brain signals, no needed additional robot intelligence, user is as much as possible, in charge and control over their left or right turning movements. In [18] a direct control noninvasive BCI system is used to design and test portable noninvasive brain computer interface that makes possible the continuous direct control of a mobile robot in a house like environment. The interface uses 8 surface electrodes to measure EEG signals from which a statistical classifier recognizes 3 different mental states, where after a few days of training, two users were able to successfully apply mental control to move a robot inside home of several rooms, moreover, comparing to manual control, mental control was only marginally worse in performing the same task. In [49] a direct control noninvasive BCI is applied to design and implement a brain controlled robot to yield four different directional movements (forward, backward, right and left). It was used single electrode pair acquisition was used, robot module and ARM controller based driving unit

In [50] is proposed an EEG based wireless mobile robot control applying direct control with a noninvasive BCI. the robot can be controlled by human eye blink strength and attention level. To control different mental fatigue, a closed neurofeedback loop is used. neurosky Mindwave single channel prototype sensor was used to acquire EEG signal. Different detected movements including right, left, forward, backward, stop positioned on eye blink strength. In [51] a synchronous operant conditioning BCI is developed, as well as, all computational methods and necessary techniques to identify mental activities. BCI is used to initiate the movements of a 120lb mobile robot, associating four different mental activities to robot commands. The BCI uses intuitive mental activities such as imaginary movement of the left arm to turn the robot left.

A typical example of applying shared control technique include; In [52] shared control by the noninvasive BCI is applied to control wheelchair, the wheelchair designed with ultrasonic sensor to detect the obstacles and accelerator sensor (MEMS) to calculate the amount of acceleration tilt to help navigate on ramps and slopes and control the movements. In [53] a shared control system is applied to control a wheelchair, with a steady-state visual evoked potential SSEP BCI that issues four motor commands; turning left , turning right, going forward and going backward. wheelchair had an autonomous navigation system that safely executes the issued commands. In [54] Shared control using a P300 BCI is applied to control a wheelchair to reach the selected desired location, selected from a list of predefined locations, this selected location is then sent to an autonomous system, that in turn drives the wheelchair to the desired locations in a known environment. In this system, user is able to stop wheelchair movement at any time by ERD/ERS BCI or a fast P300 BCI. In [55] Shared control is applied to combine a P300 BCI and an autonomous navigation system to develop a robotic wheelchair, in an unknown environment. By focusing attention user is able to control the wheelchair motion (stop wheelchair, turn left or right.

In [56] authors present a shared control architecture that couples the intelligence and desires of the user with the precision of a powered wheelchair. The research show how four healthy subjects are able to master control of the wheelchair using an asynchronous motor–imagery based BCI protocol and how this results in a better and higher overall performance, compared with alternative synchronous P300–based approaches. In [57] is introduced a shared control system that helped the subject in driving an intelligent wheelchair with a noninvasive brain interface. The subject's steering intentions were estimated from EEG signals and passed through to the shared control system before being sent to the wheelchair motors [1].

In [58] a slow P300-based BCI is used to select a destination among a list of predefined locations and a faster MI-based BCI to stop the wheelchair, which provides mobility to BCI users in a safe way. In [59] developed an adaptive shared control system of a brain-actuated simulated wheelchair aiming at providing an extra assistance when a subject was in difficult situations. the shared control include three possible discrete mental steering commands of forward, left, and right, and three levels of automatic control assistance, including collision avoidance, obstacle avoidance, and orientation recovery, would be triggered whenever the user had difficulties in driving the wheelchair towards the goal [1].

In [60] utilizing the alpha brain waves particularly detecting and controlling the amplitude of the alpha brain waves, author describes the development and testing of an interface system whereby user can control external physical devices by voluntarily controlling alpha waves, that is through eye movement. Such a system can be used for the control of external physical devices like prosthetics, robotic arms and wheelchairs using the alpha brain waves and the Mu rhythm. Control Based on pattern generation, as implemented in [61] work permits creativity to be expressed by the generation of artistic images. A subject modulates his or her sensory motor rhythms, SMRs with the aim of creating artistic representations by controlling the motion of two moving robots[61].

3.1.4.2 Brain-controlled manipulators

Manipulator mainly refers to a variety of robot arms and mechanical prosthetics. Most of the manipulators have a relatively small DOF, which are able to imitate a human's arm to finish different kinds of tasks [1].

Brain-controlled manipulators can be classified into two classes ("Fig. 10"), *i)* brain-controlled robotic manipulators (e.g. robotic arm and a semi-autonomous assistive robot,) and, *ii)* BCI based prosthetic limbs (neuroprosthetic devices).

It is suggested that EEG based BCI can provide accurate and reliable control of a robotic manipulator, the speed and accuracy of the control can be improved using electrocorticographic activity control signals [62].

One representative work of brain-controlled manipulators is the manipulator used within the FRIEND system developed in [63] [64] which is able to show the brain controlled capabilities of robots out of a controlled laboratory situation [20]. In [65] to control a 7- DOF wheelchair-mounted robotic, arm author applied a P300 BCI. The BCI interface consists of 15 stimuli corresponding to 14 movements of the robot arm and one stop command, which interpret the user's intention to direct the robot along a step-by-step path to a desired position. In [66] proposed a BMI system to perform the motion of a serial manipulator in the whole workspace. Based on motor imagery and shared control, Small-world neural network (SWNN) was used to classify five brain states [1]. In [67] demonstrate a BCI for the control of a wheelchair-mounted robotic arm system. Monkeys were trained to move a brain controlled robot arm in Virtual reality. Researchers have also succeeded in assisting them to eat with a real robot arm [68]. In [69] implemented mind controlled robotic arm to yield different movements in robotic arm.

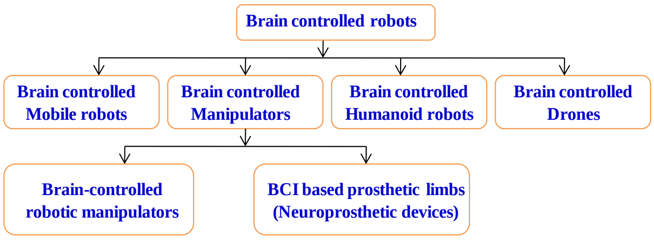

Fig. 10: The classes of Brain-controlled manipulators

3.1.4.2.1 BCI based prosthetic limbs (Neuroprosthetic devices /Neuromotor Prostheses).

The researches in this field are directed to use a EEG based BCI signals for controlling movement of limbs and to restore motor function in tetraplegics or amputees. To restore or improve normal functionality, for patients who have mobility or communication issues, specially who cannot recover previous levels. EEG based BCI signals might be used to activate a device that activates functional electrical stimulation (FES) or assistive robotics including prosthetic limbs, (neuroprosthetic devices).

The motor imagery (MI) task is one approach applied in this field, where the user is asked to imagine a movement of either the right or left hand. By doing so, a locally confined response can be detected in the EEG signal. After calculating a classifier, the system can detect which limb was imaginary moved by the user [7].

In [70] authors developed a low cost EEG based BCI prosthetic using Motor imagery MI, and realized the open or close of the whole hand by detecting the left or right Motor imagery. In [71] using EEG based BCI signals, a partially paralyzed human was able to open and close a prosthetic hand, and use a simple multijointed robotic limb to grasp and transport objects via intracortical electrodes. In [72] authors applied non-invasive techniques to restore grasp functionality in a tetraplegic patient through functional electrical stimulation FES. In [73] proposed design of Noninvasive brain-computer interface driven hand orthosis. In [74] Design and development of the cable actuated finger exoskeleton for hand rehabilitation following stroke. In [75] noninvasive brain-machine interface system to restore gait function in humans is analyzed. In [76] propose an on-line EEG-based BCI system for controlling the hand movement in a virtual reality environment Using Real-Time Recurrent Probabilistic Neural Network.

3.1.4.3 Brain-controlled humanoid robots.

EEG based BCI is an unlikely candidate to be applied for more complex forms of control because of its low signal-to-noise ratio. a new BCI challenging field is to control humanoid robot to perform complex tasks such as walking to specific locations and picking up desired objects.

In [77] authors applied asynchronous direct control to develop a BCI based humanoid robot control system. The system consists of an EEG, a humanoid robot, and a CCD camera. The goal of the study is to control humanoid walking behavior through neural signals acquired by the 32 channel EEG. Three types of robot walking behaviors are implemented, turning right, turning left and walking forward. In [78] is described a new humanoid navigation system that is directly controlled through an asynchronous sensorimotor rhythm-based direct-control BCI system. An indoor maze was used to test the robot, the experimental testing procedures consist of parts; offline training, online feedback testing, and real-time control sessions. In [79] Control of a humanoid robot by a noninvasive brain computer interface in humans, leveraging advances in robotics. To issue commands to control a partially autonomous humanoid robot to perform complex tasks (e.g. walking to specific locations and picking up desired objects.), EEG based interface and Visual feedback from the robot's cameras were used. Using the visual feedback , the user can select an objects in the surrounding for pick-up and transport to chosen locations.

3.1.4 Drone Control

Nowadays, because of its flexibility and diversity, Drones becoming popular and widely used in different field, including transportation, entertainment and even in air shooting.

In [80] were established on an air swimmer drone vehicle, an steady-state visual evoked potentials SSVEPs-based BCI system using fuzzy tracking and control algorithm. The drone was able to implement different movements including elevate, dive, turn left, go forward, and turn right. The system aims at helping subjects with amyotrophic lateral sclerosis ALS, participate in communication or entertainment [1]. In [81] authors realized a quadcopter control in three-dimensional space using a noninvasive MI-based BCI. The subject could pilot the AR Drone Quadcopter safely through suspended-foam rings with the help of the visual feedback of the quadcopter's video on the computer screen.

3.2 NeuroEntertainment

The human's brain emits an electrical charge in response to rhythmic sensory stimulation, through the ears, eyes or other senses. These electrical responses become what human see and hear. Different commercial companies take advantage of brain signals. EEG based commercial application fields include Neurogaming, Neurotoys, Art, and Virtual reality as shown in "Fig. 11 " .

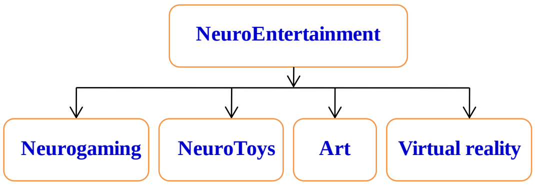

Fig. 11: Application usage field of EEG in NeuroEntertainment

3.2.1 NeuroGaming

NeuroGaming is to interact with the game without direct physical contact using EEG based BCI. The first application of non-medical EEG based BCIs were in the field of gaming/entertainment, where the first stand-alone games came out to the market in 2009 [81][9]. NeuroGaming Clinical applications include, helping improve memory or concentration or employing serious games for emotional control and/or neuroprosthetic rehabilitation. In [83], Brainball game is designed to drop the stress level where user can only move the ball by relaxing and thus learn to control their stress[20]. Various games are designed and presented to provide interesting and fun entertainment, examples include, moving objects. In [84] a helicopters are made to fly to any point in either a 2D or 3D virtual world. In [85] the control of an animated character in an immersive 3D gaming environment with steady-state visual evoked potentialss (SSVEPs)[86].

3.2.2 NeuroToys

EEG based BCI is applied in designing toys, used for education, rehabilitation and entertainment; examples include Puzzlebox and Star wars-themed toys.

3.2.3 Art

EEG based art is the use of EEG technology for doing and designing brain controlled art, visual and music. In [87] artist interacts and manipulates dishes of water to reveal zen-like vibrations. In [88] EEG technology is used as Visualization tool to achieve and visualize drawing.

3.2.4 Virtual reality

As noted, EEG based technology make use of virtual reality in many application. Combining virtual reality with EEG technology, especially in the area of interaction techniques. in Rehabilitation and Restoration as in [42]. E.g. used to report the motion sickness level In virtual reality rehabilitation approach, patients retraining brain areas by monitoring and controlling animation movement, as in [38]. In Brain-controlled manipulators, e.g. for the control robotic arm system in virtual reality as described in [67]

Combining virtual reality with EEG technology, especially in the area of interaction techniques. Virtual reality also applied in design and evaluation of BCI based prosthetic limbs (e.g., users are imaging the movement of your hand and the virtual hand is moving) and also can be pplied in NeuroEntertainment (e.g. user can navigate through houses or museums by your thoughts alone or just by looking at some highlighted objects). Furthermore, virtual reality can provide an excellent testing ground for procedures that could be adapted to real world scenarios, especially patients with disabilities can learn to control their movements or perform specific tasks in a VE. Several studies will highlight these interactions [89].

3.3 EEG-based biometry (Security and authentication)

EEG based biometry is an emerging research topic, it is using brain EEG activity as a form of brain biometric authentication information for identification of someone's identity and general cognitive state. It has higher importance in security, access control, person identification and authentication. EEG based authentication system determines whether the user is who he claims to be. Identification determines who the member is and whether he has access control [90]. The most common used EEG forms are resting state brain activity or a visual evoked potential task. Since EEG biosignals are a reflection of individual dependent inner mental tasks, therefore these biosignals are confidential, difficult to synthesize or imitate and cannot be casually acquired by external observers [20].

In [91][20]EEG biosignals are used to send covert warning when the authorized user is under external forcing conditions. In [92] EEG biosignals are used as biometrics for driver authentication using simplified driving simulator with mental-tasked condition.

3.4. Cognitive Training (neurobics)

Many aspects of training are related to the brain and its plasticity. Measuring this plasticity and the afferent changes in the brain can help to improve training methods in general [81].

Cognitive functions are brain functions that enable an individual to think and act, including working memory, attention and executive functions (e.g. decision-making). Cognitive training**,** also called brain training or brain exercise or Neurobics, is any process which exercises and improves the cognitive functions and abilities of the brain as well as, delaying and/or improving brain aging, illness or injury. Other functions include performance optimization, mindfulness, accelerate Learning, early development and enhance creativity.

In [93] authors developed EEG based Cognitive Training programs, a series of training programs using the unity 3D™ Game Engine focusing on such cognitive abilities as reaction speed, flexibility, attention span, memory and problem solving. The detection system is able to analyze the user's training performance, thus automatically channeling the user to a suitable training level.

3.5 EEG based biofeedback.

EEG can be applied to study the effects of stimuli as a function of time. In addition, collected data can be fed back to a computing system in real time for BCI and human-computer interaction (HCI) applications. This is best exemplified by neurofeedback studies. Biofeedback is developed on 'the mind over matter' concept. It is a treatment technique to train human to develop better control over certain body functions and improve their health, performance and physiological changes. Feeding back and presenting the participant's brain state (to the participant) in a compressive way will allow them to alter their brain state according to the feedback provided. This premise is the foundation of neurofeedback [93]. Neurofeedback NF, is a form of biofeedback, it is direct training of brain function used to successfully improve cognitive and physical performance of humans [94].

EEG based biofeedback application fields include medicine, educational, self-regulation and EEG Data Driven Animation.

EEG based Biofeedback is used in education, to investigate a process of information understanding, determine the degree of clearness of studied information [95], or to apply educational techniques that best work for individual students.

EEG Biofeedback is widely used for clinical purposes, including rehabilitation scenarios to treat Adult attention-deficit/hyperactivity disorder (ADHD) or Attention Deficit Disorder (ADD), as in [96], as well as children with Autism Spectrum Disorder (ASD) as in [97].New emerging applications of EEG data driven animation in e-learning, games, entertainment, and medical applications EEG data driven animation is often used in neurofeedback systems for concentration training in children and adults [98].

EEG based Biofeedback application in self-regulation, often neurofeedback techniques measure meditation or relaxation using frequency analysis (Cahn, Polich 2006). Brainball system is an example of neurofeedback, it is designed such that it informs the participant of their current brain state (relaxation) and allows the participant to act on that information [99]. Brainball is designed to drop the stress level where user can only move the ball by relaxing and thus learn to control their stress [100].Also EEG Biofeedback used to handle Mood and anxiety disorders, to improving reading disability, to improving traumatic brain injury, measure and improve the sleep quality.

In [101] demonstrated that neurofeedback was an effective treatment for anxiety disorder. Following 30 sessions of EEG biofeedback within a three-month period, patients reported a significant reduction in anxiety-related symptoms. At one-year follow-up, results of SCL-90-R showed all clinical scales within normal range. In [102] authors conclude that Neurofeedback, combined with new neuro-markers (event-related potentials and connectivity) and traditional features, promises to provide new hope for brain and cognitive training in the growing older population.

As noted, In [41] is proposed a BCI system that is able to control two different feedback devices. Also In [50] a closed neurofeedback loop is used to control different mental fatigue.

3.6 EEG-based Neuroergonomics (Human factors, ergonomics and Neuroergonomics).

The word Ergonomics is derived from two merged Greek words, 'ergon' meaning 'work' and word 'nomos' meaning laws, the both words mean 'the science of work'. According to International Ergonomics Association, both terms Ergonomics and human factors are synonymous and defined similarly as scientific field and profession. It is the scientific field concerned with the study and understanding of interactions between humans and elements of surrounding environment, to design and optimize human well-being and overall system performance, in order to design equipments, devices and processes that fit the human body and its cognitive abilities and offer safety, luxury and physiological control to humans' daily life. Ergonomics is the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance. Ergonomists contribute to the design and evaluation of tasks, jobs, products, environments and systems in order to make them compatible with the needs, abilities and limitations of people[103].

Neuroscience is defined as the study of brain structure and function. Neuroergonomics is the application of neuroscience to ergonomics.

It is concerned with dynamic interaction between brain and human in relation to performance at work and in everyday settings [104]. It evaluates how well a technology matches human capabilities and limitations [9].

In [105] Based on measuring users' inner-state based on brain signals, evaluate user experience, in order to propose seamless interfaces. Authors using 3D user interfaces investigate four constructs: workload, attention, error recognition and visual comfort. These could help to alleviate users when they interact with computers.

EEG based BCI Neuroergonomics, can be applied in the following applications; smart transportations; industrial application and home automation (environment control).

3.6.1 EEG based smart transportations

Distraction and fatigue are two main sources for driver's inattention considered as a strong cause for most traffic accidents [20]. EEG is applied to monitor and detect driver's fatigue [106] and to help drivers to assess their own levels of fatigue, therefore, prevent the deterioration of performance.

In [107] authors assessed the validity of a single-channel EEG device (TGAM-based chip) to monitor changes in driver's mental state from alertness to fatigue including driving performance. In [108] authors discussed the utilization of workload index to assess the driver's mental state. In [109] authors suggest that EEG can be applied as an objective and complementary evaluation technique to characterize and assess different Human-Computer Interfaces. This thus opens the door to a new generation of HCI, designed by exploiting EEG-based neuroergonomics.

3.6.2 EEG based industrial application

EEG can assist in improving workplace conditions by monitoring and assessment of an operator's cognitive state [110]. The ability to on-line continuously monitoring and assisting operator's cognitive state levels (fatigue, attention, and mental workload) in industrial and operational environments where wrong behavior could potentially result in hazardous situations, disasters or life-threatening situations, is under a lot of focus, most researchers aim at better assessing this state in order to optimize devices, software interfaces or entire work environments to develop smart technologies that enhance operator's safety and performance [111] and increase engagement, motivation and productivity. One example on EEG based on-line continuously monitoring and assisting operator's cognitive state levels is in power plant controllers to analyze how operator's brain responds to very monotonous environments.

The on-line continuously monitoring and assisting operator's cognitive state levels can be applied on civil airline pilots, on military pilots and on car drivers. In [112] is implemented EEG-based brain-actuated telepresence system that provides a user with presence in remote environments through a mobile robot. [113] authors proposed a new BMI paradigm which integrates an MI EEG to extract the target intention with adaptive decoder for cortical signals and a synergetic motor learning control to cope with the peripheral control of a multijoint redundant robot arm with environmental dynamics adaptation capability. The proposed method allowed for BMI controlled robot to employ different joint usage depending on the given payload systematically through the learning process.In [69] is implemented Mind Controlled Robotic Arm that can has industrial application. In case of accuracy could be increased, the robot arm could be successfully controlled in a real world situation.

3.6.3 EEG based home automation (environment control)

EEG based BCI technology could significantly improve the quality of life of severely disabled people when is applied in the implementation of home automation/ environment control, where appliances such as thermostat, lights, television bulb, fan can be controlled.

A proof-of-concept environment control system (A BCI-Based environmental controller for the motion-disabled) based on steady-state visual evoked potentials (SSVEPs) is described in [114]. In [115] the control of a virtual apartment with a BCI using the evoked P300 component.

The study in [116] and [117] integrated EEG based BCI technology into a domestic environmental control system, allowing patients (suffering from muscular dystrophy or atrophy) to remotely operate lights, home entertainment, front door opener, a motorized bed and telephone, as well as monitor their surroundings using wireless cameras. In [13] EEG based system is proposed to monitor and control the home appliances using IOT, meditation signals values are were used for controlling the home appliances, appliances were on/off controlled using Microcontroller. In [118] present a smart home automation system using BCI, to control and monitor home appliances from graphical user interface using brain–computer interface that use an input source and being controlled wirelessly, the design allow disabled to comfortably operate or handle the home appliances.

3.7 EEG based Neuromarketing and Advertisement

Neuromarketing is the field that observes and use human's bio-markers such as eye-tracking, bloodflow, facial expressions, brain waves, respiratory rate, heart rate, to determine how effective marketing is?. EEG based Neuromarketing, study the brain's responses to marketing stimuli (e.g. product packaging and design, websites and software interfaces) in order to identify roadblocks and improve workflows

In [119] authors show how EEG methodologies could be related to memorization and attention while people are watching marketing-relevant stimuli, and employed to better design new products. In [120] based on performed EEG experiments, suggest that the presence of a narrative structure in video commercials has a critical impact on the preference for branding products. In [121] high resolution EEG techniques are used to study brain activity during the observation of commercial advertising. In [122] present a novel preference-based measurement of user aesthetic preference recognition of 3D shapes using EEG and make buying decisions.

4. CURRENT AND FUTURE RESEARCH TRENDS

The difficulties in translating BCI technologies- the main goal of researches in EEG based BCI field is to develop systems that can be used by disabled users as direct communication pathway system with the world for communication, entertainment and control, to allow disabled to communicate with other persons, to control artificial limbs, or to control their environment. At present day, most of BCI research and development achievements, remain limited to controlled laboratory situation. The translation of the exciting laboratory achievements to peoples' daily lives is of great importance. As an example Brain controlled robots are still limited to controlled laboratory environment and not yet ready to be used, tested and validated in real world situations. This is because the BCI is not stable due to the nonstationary nature of the EEG signals. Thus, to make these mobile robots usable in real-world situations, stable BCI systems need to be explored how to improve the robustness of BCI to make it more reliable technology.

Clinical/translational research-The investigational studies currently use experimental grade BCI hardware and software that were developed for basic research and suffer from high cost and complexity, proprietary standards, and lack of robustness [123]. It is very challenging to translate this experimental-grade BCI hardware and software into product-grade clinical BCI instrumentation.

It requires the integration of BCI hardware and software into clinical environments as well as improvements to clinical applicability, robustness, usability, and cost/benefit ratio [124].

Consumer products- The typical research-based BCI system cost is about 5000 USD, which is very expensive for consumer products. Reducing these costs is mainly a technical problem that can be solved, e.g. by design and development not expensive hardware including 'dry' and 'active' electrodes,

The signal detecting, processing, generating and data analyzing are the most challenging and worthy researching tasks. More and more researchers focus their attention on discovering new evoking mechanisms and testing novel decoding algorithms [1]. In signal processing, the trend in EEG units is undoubtedly for higher sampling frequencies and more recording channels. Another trend to increase in the sampling resolution, most commercial EEG units use 16 or more bits.

Fast response and decision-making is critical in the field of brain actuated devices, especially robots and Neuroprostheses, therefore one of the most challenging issues is real-time control. To improve and guarantee overall system performance (especially robustness) and safety, other shared control techniques can be developed.

Evaluating and comparing performance of various brain-controlled mobile robots are hard and complex. To make the evaluation and comparison more reasonable, standardized performance evaluation should be established, and the related issues including subjects, tasks and environments, and evaluation metrics should be comprehensive and specified [44].

The development of EEG based BCI home automation and environmental control system in the life of both disabled of non-paralyzed humans.

5. CONCLUSIONS

Increasing number of researchers and developers are currently interested in various EEG based BCI applications.

The current work presents a review of the application areas that may use of EEG based BCI technology to assist in achieving their tasks and purpose. The scope of work emphasizes medical and biomedical engineering application areas, with a focus on researches in the field of brain controlled robotic systems; classification, techniques, and tasks.

This review intends to help researchers with interest in EEG based BCI and their theories, principles, applications and trends by putting most of it in one place. In addition, it presents research and development examples done in different application fields of the EEG based BCI systems.

REFERENCES

[1] Xiaoqian Mao, Mengfan Li, Wei Li, Linwei Niu, Bin Xian, Ming Zeng, Genshe Chen, Progress in EEG-Based Brain Robot Interaction Systems, Computational Intelligence and Neuroscience Volume 2017, Article ID 1742862, 25 pages

[2] Rao R.P.N. and Scherer R. Brain computer interfacing. *IEEE Signal Processing Magazine,* vol.

27(4), pages 152-150,2010 .

[3] W. Khalifa, A. Salem, M. Roushdy and K. Revett, "A survey of EEG based user authentication schemes," *2012 8th International Conference on Informatics and Systems (INFOS), Cairo, 2012, pp. BIO-55-BIO-60.*

[4] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. Braincomputer interfaces for communication and control. Clinical Neurophysiology, 113(6):767–791, 2002.

[5] T. M. Vaughan, W. J. Heetderks, L. J. Trejo, W. Z. Rymer, M. Weinrich, M. M. Moore, A. Kubler, ¨ B. H. Dobkin, N. Birbaumer, E. Donchin, E. W. Wolpaw, and J. R. Wolpaw. Brain-computer interface technology: a review of the second international meeting. IEEE Transactions on Neural Systems and Rehabilitation Engeneering, 11(2):94–109, 2003

[6] A. Kavitha Rajesh, EEG based machine control, international jornal of innovation in engineering and technology, Vol. 2, Issue 4, August 2013.

[7] Irimia D.C., Ortner R., Krausz G., Guger C., Poboroniuc M.S, BCI Application in Robotics Control, Proceedings of the 14th IFAC Symposium on Information Control Problems in Manufacturing Bucharest, Romania, May 23-25, 2012

[8] Rina R Wehbe, Lennart E Nacke,An Introduction to EEG Analysis Techniques and Brain-Computer Interfaces for Games User Researchers ,In Proceedings of DiGRA 2013, DiGRA, 2013

[9] V. R. Pavitrakar, "Survey of Brain Computer Interaction", in *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, Vol. 2, Issue 4, April 2013.

[10] Jerry J. Shih, Dean J. Krusienski, Jonathan R. Wolpaw, Brain-Computer Interfaces in Medicine, Mayo Clin Proc. _ March 2012;87(3):268-279 _ doi:10.1016/j.mayocp.2011.12.www.mayoclinicproceedings.org

[11] Trevor Thompson, Tony Steffert, Tomas Ros, John Gruzelier, EEG applications for sport and performance, IEEE transactions on human-machine systems, vol. 43, no. 2, march 2013

[12] Siliveru Ramesh , K.Harikrishna J.Krishna Chaitanya, Brainwave Controlled Robot Using Bluetooth, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (An ISO 3297: 2007 Certified Organization) Vol. 3, Issue 8, August 2014.

[13] Nanditha , Smt. Christy Persya A, EEG-Based Brain Controlled Robo and Home Appliances, International Journal of Engineering Trends and Technology (IJETT) – Volume 47 Number 3 May 2017

[14] Rina R. Wehbe & Lennart Nacke , An Introduction to EEG Analysis Techniques and Brain-Computer Interfaces for Games User Researchers, Proceedings of DiGRA 2013: DeFragging Game Studies, 2013

[15] E. M. Schmidt, "Single neuron recording frommotor cortex as a possible source of signals for control of external devices," *Annals of Biomedical Engineering*, vol. 8, no. 4, pp. 339–349, 1980.

[16] M. A. L. Nicolelis, "Brain–machine interfaces to restore motor function and probe neural circuits," *Nature Reviews Neuroscience*, vol. 4, no. 5, pp. 417–422, 2003.

[17] Deepak R , K R Rachith , Kevin Leo Jacob , Prashanth Kambli,' A Survey: Usage of Brain-Machine Interface in Various Applications ',International Research Journal of Engineering and Technology (IRJET) Volume: 02 Issue: 01 | Apr-2015

[18] Jose del R. Millan, Frederic Renkens, Josep Mourino, Wulfram Gerstner, Non-Invasive Brain-Actuated Control of a Mobile Robot, Proc. of the 18th Joint International Conference on Artificial Intelligence August 9-15, 2003, Acapulco, Mexico

[19] Mak, J.N. and J.R. Wolpaw, Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects. Biomedical Engineering, IEEE Reviews in, 2009. **2**: p. 187-199.

[20] Terence W Picton, 'The P300 Wave of the Human Event-Related Potential 'Journal of Clinical Neurophysiology 9(4):456-79, November 1992

[21] S. Sutton, M. Braren, J. Zubin, and E. R. John, "Evoked-potential correlates of stimulus uncertainty," *Science*, vol. 150, no. 3700, pp. 1187–1188, 1965.

[22] D. B. D. Smith, E. Donchin, L. Cohen, and A. Starr, "Auditory averaged evoked potentials in man during selective binaural listening, "*Electroencephalography and Clinical Neurophysiology*, vol. 28, no. 2, pp. 146–152, 1970.

[23] Sarah N. Abdulkader, Ayman Atia, Mostafa-Sami M. Mostafa, Brain computer interfacing: Applications and challenges, Egyptian Informatics Journal (2015) 16, 213–230

[24] Jonathan R. Wolpaw et al. Brain-computer interface research at the wadsworth center. *IEEE Transactions on Rehabilitation Engineering*, 8(2):222–226, 2000.

[25] Priyanka D. Girase , M. P. Deshmukh , A Review of Brain Computer Interface' 'International Conference on Global Trends in Engineering, Technology and Management (ICGTETM-2016)

[26] Allison BZ, Dunne S, Leeb R. Towards practical brain-computer interfaces: bridging the gap from research to real-world applications. Springer; 2012

[27] Maye A, Zhang D, Wang Y, Gao S, Engel AK.

Multimodal brain-computer interfaces. Tsinghua Sci Technol 2011;16(2): 133–9.

[28] Marcel C.M Bastiaansen, Cornelis H.MBrunia, Anticipatory attention: an event-related desynchronization approach, Volume 43, Issue 1, December 2001, Pages 91-107

[29] Pfurtscheller G, Lopes da Silva FH. Event-related eeg/meg synchronization and desynchronization: basic principles. Clin Neurophysiol 1999;110(11):1842–57

[30] Marcel C.M Bastiaansen, Cornelis H.MBrunia, Anticipatory attention: an event-related desynchronization approach, Volume 43, Issue 1, December 2001, Pages 91-107

[31] Bell C.J., Shenoy P., Chalodhorn and Rao R.P.N. Control of a humanoid robot by a noninvasive braincomputer interface in humans. *Journal of Neural Engineering*, vol. (5), pages 214-220,2008 .

[32] 32 Holly Duncan, Kate Spillane, Ian Morrison, 'Electroencephalography: An Overview', Scottish Universities Medical Journal, Vol. 3 ,Issue 1, 2014 .

[33] Hanafiah ZM, Taib MN, Hamid N. EEG pattern of smokers for theta, alpha and beta band frequencies. In: Research and Development (SCOReD), 2010 IEEE Student Conference on. IEEE; 2010. p. 320–23.

[34] Di D, Zhihua C, Ruifang F, Guangyu L, Tian L. Study on human brain after consuming alcohol based on eeg signal. In: Computer Science and Information Technology (ICCSIT), 20103rd IEEE International Conference on, vol. 5. IEEE; 2010. p. 406–09.

[35] Wolpaw, J.R., et al., Brain-computer interface technology: a review of the first international meeting. Rehabilitation Engineering, IEEE Transactions on, 2000. **8**(2): p. 164-173.

[36] Wolpaw, J.R., et al., Brain-computer interface technology: a review of the first international meeting. Rehabilitation Engineering, IEEE Transactions on, 2000. **8**(2): p. 164-173.

[37] Daly, J.J. and J.R. Wolpaw, *Brain–computer interfaces in neurological rehabilitation.* The Lancet Neurology, 2008. **7**(11): p. 1032-1043.

[38] C Neuper, G.R Müller, A Kübler, N Birbaumer, G Pfurtscheller Clinical Neurophysiology, Volume 114, Issue 3, March 2003, Pages 399-409

[39] Diana Valbuena, Marco Cyriacks, Ola Friman, Ivan Volosyak and Axel Gr¨aser, Brain-Computer Interface for high-level control of rehabilitation robotic systems, Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, June 12-15, Noordwijk, The Netherlands

[40] Hu, X.L.; Tong, K.Y.; Li, R.; Chen, M.; Xue, J.J.; Ho, S.K.; Chen, P.N. Post-stroke wrist rehabilitation assisted with an intention-driven functional electrical stimulation (FES)-robot system. In *Proceedings of the IEEE International Conference on Rehabilitation Robotics(ICORR'11)*, Zurich, Switzerland, July 2011; pp. 1–6.

[41] Ortner R., Ram D., Kollreider A., Pitsch H., Wojtowicz J., Edlinger G. (2013) Human-Computer Confluence for Rehabilitation Purposes after Stroke. In: Shumaker R. (eds) Virtual, Augmented and Mixed Reality. Systems and Applications. VAMR 2013. Lecture Notes in Computer Science, vol 8022. Springer, Berlin, Heidelberg

[42] King CE, Wang PT, Mizuta M, Reinkensmeyer DJ, Do AH, Moromugi S, Nenadic Z. Noninvasive brain-computer interface driven hand orthosis. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE. IEEE; 2011. p. 5786–89.

[43] X. Perrin, "Semi-autonomous navigation of an assistive robot using low throughput interfaces," Ph.D. dissertation, ETHZ, Zurich, Switzerland, 2009.

[44] luzheng Bi, Xin-an Fan, Yili liu, eeg-based brain-controlled mobile robots: a survey, ieee transactions on human-machine systems, vol. 43, no. 2, march 2013

[45] YoungJae Song, Francisco Sepulveda, "A novel onset detection technique for brain–computer interfaces using sound-production related cognitive tasks in simulated-online system", *Journal of Neural Engineering*, vol. 14, pp. 016019, 2017, ISSN 1741-2560.

[46] Mak, J.N. and J.R. Wolpaw, Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects. Biomedical Engineering, IEEE Reviews in, 2009. **2**: p. 187-199.

[47] J. d. R. Millan, F. Renkens, J. Mouri˜no, and W. Gerstner, "Noninvasive brain-actuated control of a mobile robot by human EEG," *IEEE Trans. Bio. Eng.*, vol. 51, no. 6, pp. 1026–1033, Jun. 2004.

[48] G. Vanacker, J. del R. Mill´an, E. Lew, P. W. Ferrez, F. G. Moles, J. Philips, H. V. Brussel, and M. Nuttin, "Context-based filtering for brain-actuated wheelchair driving," *Comput. Intell. Neurosci.*, vol. 2007, pp. 1–12, May 2007.

[49] V parthasarathy,g saravana kumar, s sivasaravana babu,grimm christoph, brain computer interface based robot design, journal of theoretical and applied information technology, 28th february 2015. vol.72 no.3

[50] Stephygraph L.R., Arunkumar N. (2016) Brain-Actuated Wireless Mobile Robot Control Through an Adaptive Human–Machine Interface. In: Suresh L., Panigrahi B. (eds) Proceedings of the International

Conference on Soft Computing Systems. Advances in Intelligent Systems and Computing, vol 397. Springer, New Delhi

[51] Alexandre O. G. Barbosa, David R. Achanccaray, and Marco A. Meggiolaro,' Activation of a Mobile Robot through a Brain Computer Interface', 2010 IEEE International Conference on Robotics and Automation, Anchorage Convention District, May 3-8, 2010, Anchorage, Alaska, USA

[52] V. Jeyaramya, A. Asline Celes, Mind -Controlled Wheel Chair using an EEG Probes using Microcontroller, International Journal for Innovative Research in Science & Technology, Volume 2 , Issue 10 , March, 2016

[53] C. Mandel, T. Luth, T. Laue, T. Rofer, A. Graser, and B. Krieg-Bruckner, "Navigating a smart wheelchair with a brain–computer interface interpreting steady-state visual evoked potentials," in *Proc. Conf. Rec. 2009, IEEE/RSJ Int. Conf. Intell. Robots Syst.*, St. Louis, MO, pp. 1118–1125.

[54] B. Rebsamen, E. Burdet, C. Guan, H. Zhang, C.L. Teo, Q. Zeng, M. Ang, and C. Laugier, "A brain controlled wheelchair based on P300 and path guidance," in *Proc. IEEE/RAS-EMBS Int. Conf. Biomed. Robot. Biomechatronics*, 2006, pp. 1001–1006.

[55] I. Iturrate, J. M. Antelis, A. Kubler, and J. Minguez, "A noninvasive brain-actuated wheelchair based on a p300 neurophysiological protocol and automated navigation," *IEEE Trans. Robot.*, vol. 25, no. 3, pp. 614–627, Jun. 2009.

[56] Tom carlson, Jos´e del r. Mill´an, brain–controlled wheelchairs: a robotic architecture, IEEE Robotics and Automation Magazine. 20(1): 65 – 73, March 2013.

[57] G. Vanacker, R. Del M J, E. Lew et al., "Context-based filtering for assisted brain-actuated wheelchair driving," *Computational Intelligence & Neuroscience*, vol. 2007, article 3, 2007.

[58] B. Rebsamen, C. Guan, H. Zhang et al., "A brain controlled wheelchair to navigate in familiar environments," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 6, pp. 590–598, 2010.

[59] J. Philips, J. D. R. Mill´an, G. Vanacker et al., "Adaptive shared control of a brain-actuated simulated wheelchair," in Proceedings of the IEEE 10th International Conference on Rehabilitation Robotics (ICORR '07), pp. 408–414, Noordwijk, Netherlands, June 2007.

[60] Rohan Hundia, Brain Computer Interface-Controlling Devices Utilizing The Alpha Brain Waves, international journal of scientific & technology research volume 4, issue 01, January 2015.

[61] Paola Belluom, Maide Bucolo ,Luigi Fortuna ,Mattia Frasca "Robot Control through Brain-Computer Interface for Pattern Generation", Complex Systems, 20 © 2012 Complex Systems Publications, Inc.

[62] D.J.McFarland J.R.Wolpaw,'EEG-based brain–computer interfaces', Current Opinion in Biomedical Engineering Volume 4, December 2017, Pages 194-200

[63] S. M. Grigorescu, T. L¨uth, C. Fragkopoulos, M. Cyriacks and A. Gr¨aser, "A BCI controlled robotic assistant for quadriplegic people in domestic and professional life," *ROBOTICA*, vol. 30, no. 3, pp. 419–431, 2011.

[64] H. Cecotti and A. Graser, "Convolutional neural networks for P300 detection with application to brain–computer interfaces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 3, pp. 433–445, Mar. 2011.

[65] M. Palankar, K. J. De Laurentis, R. Alqasemi et al., "Control of a 9-DoF wheelchair-mounted robotic arm system using a P300 brain computer interface: initial experiments," in *Proceedings of the IEEE International Conference on Robotics and Biomimetics(ROBIO '08)*, pp. 348–353, February 2009.

[66] T. Li, J. Hong, J. Zhang et al., "Brain-machine interface control of a manipulator using small-world neural network and shared control strategy," *Journal of Neuroscience Methods*, vol. 224, no. 6, pp. 26–38, 2014.

[67] Y. Arbel, R. Alqasemi, R. Dubey, and E. Donchin, "Adapting the P300- brain computer interface (BCI) for the control of a wheelchair-mounted robotic arm system," *Psychophysiology*, vol. 44, no. S1, pp. S82–S83, 2007.

[68] MULLER K-R, Kubler A. Toward brain computer interfacing Massachusetts Institute of Technology 2007:1–25.

[69] Devashish Salvekar, Amrita Nair, Dany Bright, Prof.S.A.Bhisikar, 'Mind Controlled Robotic Arm 'Journal of Electronics and Communication Engineering 2278-8735. pp 36-44, NCIEST-2015

[70] D. Elstob and E. L. Secco, "A low cost eeg based BCI prosthetic using motor imagery," International Journal of Information Technology Convergence and Services, vol. 6, no. 1, pp. 23–36, 2016.

[71] Hochberg, L.R., et al., Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature, 2006. 442(7099): p. 164-171.

[72] G. Pfurtscheller, G.R. M¨uller, J. Pfurtscheller, H.J. Gerner, and R. Rupp. Thoughtcontrol of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. *Neuroscience Letters*, 351(1):33–36, 2003.

[73] King CE, Wang PT, Mizuta M, Reinkensmeyer DJ, Do AH, Moromugi S, Nenadic Z. Noninvasive brain-computer interface driven hand orthosis. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE. IEEE; 2011. p. 5786–89.

[74] Jones CL, Wang F, Morrison R, N.Sarkar N, Kamper DG. Design and development of the cable actuated finger exoskeleton for hand rehabilitation following stroke. IEEE Syst J 2014.

[75] Presacco A, Forrester L, Contreras-Vidal JL. Towards a noninvasive brain-machine interface system to restore gait function in humans. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE. IEEE; 2011. p. 4588–91.

[76] Mohammad Ahmadi and Abbas Erfanian, ―An On-Line BCI System for Hand Movement Control Using Real-Time Recurrent Probabilistic Neural Network‖, Proceedings of the 4th International IEEE Conference on Neural Engineering, pp. 367 – 370, Antalya, Turkey, April 29 - May 2, 2009

[77] Wei Li, Christian Jaramillo, Yunyi Li, brain computer interface based humanoid robot control system *Proceedings of the IASTED International Conference November 7 - 9, 2011 Pittsburgh, USA*

[78] yongwook chae, jaeseung jeong, , sungho jo, toward brain-actuated humanoid robots: asynchronous direct control using an eeg-based bci, IEEE transactions on robotics, 2012 IEEE.

[79] C. J Bell, P. Shenoy, R. Chalodhorn, and R. P. N Rao, “Control of a humanoid robot by a noninvasive brain–computer interface in humans,” *J. Neural Eng.*, vol. 5, no. 2, pp. 214–220, May 2008.

[80] Y. Chen, S. Chen, I. Zaeni, and C. Wu, “Fuzzy tracking and control algorithm for an SSVEP-based BCI system,” *Applied Sciences*, vol. 6, no. 10, article 270, 2016.

[81] K. Lafleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, “Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain-computer interface,”

[82] Robert-bela nagy , Florin popentiu , Radu c. tarca, A survey of brain computer interface, annals of the university of oradea fascicle of management and technological engineering issue #3, december 2014, http://www.imtuoradea.ro/auo.fmte/

[83] Tan DS, Nijholt A. Brain-computer interfaces: applying our minds to human-computer interaction. Springer; 2010.

[84] Royer AS, Doud AJ, Rose ML, He B. Eeg control of a virtual helicopter in 3-dimensional space using intelligent control strategies. Neural Syst Rehabilitation Eng, IEEE Trans2010;18(6):581–9.

[85] E. Lalor, S. Kelly, C. Finucane, R. Burke, R. Smith, R. Reilly, and G. McDarby, “Steady-state VEP-based brain-computer interface control in an immersive 3D gaming environment,” *EURASIP Journal on Applied Signal Processing*, vol. 2005, no. 19, pp. 3156–3164, 2005.

[86] T. Ebrahimi, "Recent advances in brain-computer interfaces", 2007 IEEE 9th Workshop on Multimedia Signal Processing, pp. 17-17, Oct 2007.

[87] https:// creators.vice. com/en_us/article/ vvygzm/ eunoia- seeking-enlightenment -by-tracking-brainwaves

[88] http://naotohieda.com/muse/

[89] Lotte F. et al. (2012) Combining BCI with Virtual Reality: Towards New Applications and Improved BCI. In: Allison B., Dunne S., Leeb R., Del R. Millán J., Nijholt A. (eds) Towards Practical Brain-Computer Interfaces. Biological and Medical Physics, Biomedical Engineering. Springer, Berlin, Heidelberg

[90] G. Elakkiaa P. Sripriyab and R. Devi,’ A Review on EEG based Biometric Identifi cation of Human ’ International Journal of Control Theory and ApplicationsVolume 10 ,Number 23, 2017

[91] Su F, Zhou H, Feng Z, Ma J. A biometric-based covert warning system using EEG. In: Biometrics (ICB), 2012 5th IAPR International Conference on. IEEE; 2012. p. 342–47.

[92] Nakanishi I, Baba S, Li S. Evaluation of brain waves as biometrics for driver authentication using simplified driving simulator. In: Biometrics and Kansei Engineering (ICBAKE), 2011 International Conference on. IEEE; 2011. p. 71–76.

[93] Zhipeng Huang, Yingjie Li ,Wanlin Dong ,Wenxi Li Purdue , XiaoliYang , Cognitive Training Programs with EEG Headset, Proceedings of The 2016 IAJC-ISAM International Conference.

[94] Pfurtscheller G., Müller-Putz G. R., Scherer R., Neuper C. (2008). Rehabilitation with brain-computer interface systems. Computer 41, 58–65. 10.1109/mc.2008.432

[95] Kirill Sorudeykin,; An Educative Brain-Computer Interface’, IEEE East-West Design & Test International Symposium, Moscow, September 2009

[96] Gevensleben, Holger, Holl, Birgit, Albrecht, Björn, Vogel, Claudia, Schlamp, Dieter, Kratz, Oliver, Studer, Petra, Rothenberger, Aribert, Moll, Gunther H and Heinrich, Hartmut, 2009, Is neurofeedback an efficacious treatment for ADHD? A randomised controlled clinical trial. Journal of child psychology and psychiatry, and allied disciplines online. July 2009. Vol. 50, no. 7, p. 780–9.

[97] Kouijzer, MEJ and Moor, JMH de, 2009, Neurofeedback improves executive functioning in

children with autism spectrum disorders. … Spectrum Disorders online. 2009. Vol. 1, p. 145–162.

[98] Sourina O., Sourin A., Kulish V. (2009) EEG Data Driven Animation and Its Application. In: Gagalowicz A., Philips W. (eds) Computer Vision/Computer Graphics CollaborationTechniques. MIRAGE 2009. Lecture Notes in Computer Science, vol 5496. Springer, Berlin, Heidelberg

[99] Hjelm, Sara Ilstedt, 2003, *The Making of Brainball*. Stockhom, Sweden.

[100] Tan DS, Nijholt A. Brain-computer interfaces: applying our minds to human-computer interaction. Springer; 2010.

[101] Afsaneh Moradi, Pouladi, Nooshin Pishva, Bagher Rezaei, Maliheh Torshabi, Zahra Alam Mehrjerd,' Treatment of Anxiety Disorder with Neurofeedback: Case Study ',Procedia - Social and Behavioral Sciences, Elsevier, 2011

[102] Jiang, Yang, Reza Abiri, and Xiaopeng Zhao. "Tuning Up the Old Brain with New Tricks: Attention Training via Neurofeedback." *Frontiers in Aging Neuroscience* 9 (2017): 52. *PMC*. Web. 2 Mar. 2018.

[103] International Ergonomics Association. *What is Ergonomics*. Website. Retrieved 17 March 2014.

[104] Ranjana K. Mehta, Raja Parasuraman, 2013, 'Neuroergonomics: a review of applications to physical and cognitive work', Frontiers in Human Neuroscience, vol. 7

[105] Jérémy Frey, Martin Hachet, Fabien Lotte. EEG-based neuroergonomics for 3D user interfaces: opportunities and challenges. Le travail humain, Presses Universitaires de France, 2016.

[106] Wang Q, Wang H, Zhao C, Yang J. Driver fatigue detection technology in active safety systems. In: Remote Sensing, Environment and Transportation Engineering (RSETE), 2011 International Conference on. IEEE; 2011. p. 3097–3100.

[107] José M. Morales, Carolina Díaz-Piedra, Héctor Rieiro, Joaquín Roca-González, Samuel Romero, Andrés Catena, Luis J. Fuentes, Leandro L. Di Stasi, Monitoring driver fatigue using a single-channel electroencephalographic device: A validation study by gaze-based, driving performance, and subjective data, Accident Analysis & Prevention, Volume 109, Pages 62-69, 2017,

[108] Borghini G, Vecchiato G, Toppi J, Astolfi L, Maglione A, Isabella R, Caltagirone C, Kong W, Wei D, Zhou Z et al. Assessment of mental fatigue during car driving by using high resolution eeg activity and neurophysiologic indices. In: Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE. IEEE; 2012. p. 6442–45.

[109] Jérémy Frey, Martin Hachet, Fabien Lotte. Recent advances in EEG-based neuroergonomics for Human-Computer Interaction. 1st International Neuroergonomics conference, Oct 2016, Paris, France. Proceedings of the 1st International Neuroergonomics conference

[110] Venthur B, Blankertz B, Gugler MF, Curio G. Novel applications of bci technology: psychophysiological optimization of working conditions in industry. In: Systems Man and Cybernetics (SMC), 2010 IEEE International Conference on. IEEE; 2010. p. 417–21.

[111] Parasuraman, R., Christensen, J. and Grafton, S. (2012). Neuroergonomics: The brain in action and at work, NeuroI-mage, 59, 1-3.

[112] T.Shanmugapriya, S.Senthilkumar, A Telepresence Mobile Robot Controlled With a Non-Invasive Brain-Computer Interface, International Journal of Innovative Research in Computerand Communication Engineering Vol. 1, Issue 4, June 2013.

[113] Saugat Bhattacharyya, Shingo Shimoda, Mitsuhiro Hayashibe. A Synergetic Brain-Machine Interfacing Paradigm for Multi-DOF Robot Control. IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, Institute of Electrical and Electronics Engineers, 2016, 46 (7), pp.957-968. <10.1109/TSMC.2016.2560532>. <lirmm-01347425>

[114] X. Gao, D. Xu, M. Cheng, and S. Gao, "A BCI-Based environmental controller for the motion-disabled," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 137–140, 2003.

[115] J. D. Bayliss, "Use of the evoked P3 component for control in a virtual apartment," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 113–116, 2003.

[116] Cincotti, F., et al. Non-Invasive Brain-Computer Interface System to Operate Assistive Devices. in Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE. 2007.

[117] Cincotti, F., et al., Non-invasive brain–computer interface system: Towards its application as assistive technology. Brain Research Bulletin, 2008. 75(6): p. 796-803

[118] S.P.Pande , Prof.Pravin Sen, Review On: Home Automation System For Disabled People Using BCI, Journal of Computer Science, PP 76-80, International Conference on Advances in Engineering & Technology – 2014 (ICAET-2014)

[119] Giovanni Vecchiato, Wanzeng Kong, Anton Giulio Maglione, Daming Wei, 'Understanding the impact of TV commercials: electrical neuroimaging ',IEEE Pulse 2012, 3 (3): 42-7.

[120] Regina W Y Wang, Yu-Ching Chang, Shang-Wen Chuang, EEG Spectral Dynamics of Video Commercials: Impact of the Narrative on the Branding Product Preference, Scientific Reports 2016 November 7, 6: 36487

[121] Vecchiato G, Astolfi L, De Vico Fallani F, Salinari S, Cincotti F, Aloise F, Mattia D, Marciani MG, Bianchi L, Soranzo R. The study of brain activity during the observation of commercial advertising by using high resolution EEG techniques. In: Engineering in Medicine and Biology Society, 2009. EMBC2009. Annual International Conference of the IEEE. IEEE; 2009. p. 57–60.

[122] Lin Hou Chew, Jason Teo, James Mountstephens, Aesthetic preference recognition of 3D shapes using EEG, Cognitive Neurodynamics 2016, 10 (2): 165-73

[123] Cincotti F, Bianchi L, Birch G, Guger C, Mellinger J, Scherer R, Schmidt R N, Y´a˜nez Su´arez O and Schalk G 2006 BCI meeting2005—workshop on technology: hardware and software *IEEE Trans. Neural Syst. Rehabil. Eng.* 14 128–31

[124] P Brunner, L Bianchi4, C Guger, F Cincotti4 and G Schalk, Current trends in hardware and software for brain–computer interfaces (BCIs), journal of neural engineering, 8 (2011) 025001 (7pp)