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BCI for Exoskeletons and Prostheses from Rehabilitation to Human Enhancement

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Abstract:

Brain-computer interface (BCI) technology has revolutionized the development of motor rehabilitation and body enhancement. However, a significant gap exists between the limited use of BCI for exoskeletons and prosthetics in healthy individuals and its wide application in motor-impaired patients. This literature review aims to bridge that gap and highlight the potential of BCI technology for future applications in body enhancement for healthy individuals. We review the literature across neuroscience, biomedical engineering, and robotics, focusing on BCI applications in prosthetics and exoskeletons for both motor-impaired and healthy individuals. We summarize the methods for adapting and transferring prosthetic structures designed for individuals with disabilities to healthy individuals and identify the most suitable model for the healthy population. Our findings highlight the transformative potential of BCI technology to significantly enhance human capabilities, inspire innovation in assistive devices, and improve productivity and quality of life.

Keywords:-brain computer interface (BCI); human augmentation; rehabilitation; exoskeleton; prosthetics.

1. Introduction

Humans have long been fascinated by enhancing their physical and cognitive abilities. In fiction, we often see characters with exoskeletons displaying superhuman strength and endurance. Historically, augmentation has been achieved through chemical substances or kinetic machinery setups [1]. While these methods have achieved some success, they are limited in functionality, lack control precision, and often fail to integrate seamlessly with natural human abilities. Recent advances in brain-computer interface (BCI) technology now allow direct control of external assistive devices through brain signals, offering new possibilities in this field. BCI has proven effective in motor rehabilitation, particularly in translating neural signals into commands that control prosthetics, exoskeletons, and other assistive devices [1,2]. However, research on the application of BCI for human enhancement remains limited. This paper aims to bridge the gap by examining how BCI technologies used in treatment and rehabilitation can be adapted for human enhancement. We provide an overview of BCI techniques in both fields and discuss protocols for transitioning from therapeutic applications to human enhancement. This exploration highlights the transformative potential of BCI technology to significantly enhance human capabilities and inspire innovation in the development of future devices.

2. BCI Applications in Treatment and Rehabilitation

2.1 Structure of the BCI-Prostheses System

A typical BCI workflow is as follows (see Fig.1):

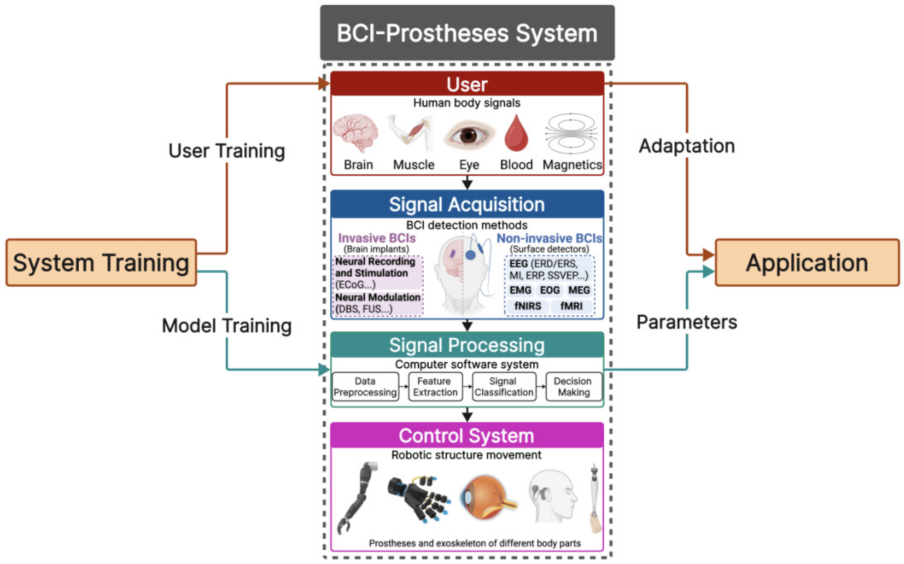

Fig.1 Flow Chart of the BCI-Prostheses System Design.

The experiment design has two stages: system training and application. System training involves user adaptation and model parameter setting. In a BCI-Prostheses system, signals are collected using various acquisition methods, processed by software, and then used to control the system.

2.1.1 Signal Acquisition

EEG was widely used in BCI rehabilitation (see Table 1). Utilizing movement-related cortical potentials (MRCPs) in an ankle-foot orthosis has been shown to enhance cortical neuroplasticity [1]. Additionally, slow cortical potentials (SCPs), such as P300, have been demonstrated to enable self-paced brain-computer interface (BCI) control for exoskeletons, albeit with a slower response time [2]. Other EEG signals like steady-state visual evoked potentials (SSVEPs), event-related potentials (ERPs), and gamma-band activity have been utilized in different scenarios. EMG complemented EEG by providing direct muscle movement information, while optical imaging like fluorescent calcium indicators measured neural activity in peripheral nerves. Multimodal acquisition with EMG and EOG improved ITR and accuracy, outperforming single-mode fNIR and MEG approaches [3,4]. However, fNIR and MEG could offer better spatial resolution than EEG.

2.1.2 Signal Processing

The signal processing process involves four major steps: In data preprocessing, raw signals are filtered and amplified to improve the signal-to-noise ratio and identification accuracy [5]. In feature extraction, Mean Square and Mean Absolute Value are ideal for EMG, while features from specific frequency bands and Power Spectral Density are crucial for EEG. Common Spatial Pattern (CSP) algorithm enhances feature discrimination by maximizing variance between signal classes [5]. In signal classification, Linear discriminant analysis (LDA) is effective for separating linear data, while support vector machines (SVM) handle non-linear data and noise. For complex EEG data, backpropagation neural networks and Directed Acyclic Graph (DAG) structures are used to classify multiclass tasks and decode user intentions from MI signals [6]. In decision-making, classified signals are translated into commands or actions, such as adjusting the gait of exoskeleton robots based on the user's intentions to climb stairs of different heights [5].

2.1.3 Control System

In mechanical hardware design, soft robotic gloves are designed to enhance hand functions through adaptable control systems. Retinal prostheses and cochlear implants translate sensory information to restore vision and hearing. Robotic legs mimic the user's gait and adapt to different terrains. 3D-printed plastic parts and servomotors have been utilized to ensure efficient power transmission while reducing the weight burden on patients [7]. Additionally, the use of an air pump has been employed to develop a robotic glove that achieves similar goals [8]. In the design of control programs, a single-pole double-throw brain switch (SPDTBS) was used to extend command numbers and improve accuracy through dual-signal detection [9].

Table.1 Different Diseases BCI-based Rehabilitation Studies.

Study	Disease type	Body part	Signal	Feedback	Result
			Upper Limb Rehabilitation		
Bundy et al (2017)	Stroke	Arm	EEG	Actions+Tactile	ARAT Increased: 6.2 points
Salvietti et al (2017)	Stroke	Finger	EMG	Actions	Total Score Increased: 2/5
Zhang et al (2019)	Stroke	Hand	EEG-EMG-EOG	Actions	CA: 93.83%
Minati et al (2017)	Stroke	Arm	EEG-EMG-EOG	Actions	CA: 95%
Asgher et al (2021)	Hemiplegia	Hand	fNIRS	Actions	CA: 91.31%
Benabid et al (2019)	Tetraplegia	Four limbs	MEG-fMRI	Muscular	VA at home: 64·0% success
			Lower Limb Rehabilitation		
Li et al (2019)	Stroke, SCI	Leg	EEG(SMRs)-EMG	Actions	ERA: over 80%
Xu et al (2014)	Stroke	Ankle–Foot	EEG (MRCPs)	Actions	True Positive Rate: 73.0%
Gao et al (2021)	Amputee	Leg	EEG (SSVEPs)	FES	CA: 81.11%
Barria et al (2021)	Stroke	Ankle	EEG (SSVEPs)	Visual+Tactile	CA: MIVH 68.0%>MIV 50.7%
Choi et al (2020)	SCI	Leg	EEG-EOG	Visual	CA: 88.4%
Ortiz et al (2020)	Stroke, SCI	Leg	EEG(SCPs)	Actions	Average CA>75%
			Sensory Rehabilitation		
Niketeghad et al (2018)	Blind	Retina	Phosphenes Perception	Vision	Light detection, shape/direction sensing
Ganzer et al (2020)	Blind	Retina	Optical Signal	Vision	Visual perception via electrical stimulation
Ganzer et al (2020)	SCI	Arm	IMA	Tactile	Tactile Perception Accuracy>90%
Tabot et al (2013)	Tetraplegia Amputee	Arm	ICMS	Tactile	Dexterity and Embodiment Increased

SCI: Spinal Cord Injury; EEG: Electroencephalography; EMG: Electromyography; EOG: Electrooculography; MEG: Magnetoencephalography; fNIRS: Functional Near-Infrared Spectroscopy; SMRs: Sensory Motor Rhythms; MRCPs: Movement-Related Cortical Potentials; VA: Virtual Avatar; SSVEPs: Steady-state visual evoked potentials; SCPs: Slow Cortical Potentials; IMA: Intracortical Microelectrode Array; CA: Classification Accuracy; ICMS: Intracortical Microstimulation; FES: Functional Electrical Stimulations; ARAT: Action Research Arm Test; ERA: EEG Recognition Accuracy; MIVH: Motor Imagination with Visual-haptic Inducement; MIV: Motor Imagination with Visual stimulation

2.2 System Training

System training involves both user and model training. To enhance user understanding of the devices, Buch et al.,[4] employed a goal-oriented visual feedback task, enabling participants to verify the accuracy of their brain signals. Similarly, a survey focusing on usability ratings after training was conducted to assess the effectiveness of the approach [7]. To optimize model parameters, EOG and EEG training models were developed, utilizing data from 10 trials per pattern to calculate thresholds and refine classifier parameters [8]. In addition to the traditional BCI-prostheses system, researchers conducted somatosensory attentional orientation (SAO) training tasks to improve system performance through sensory stimulation [10]. Noticeably, tactile stimulation can improve signal calibration efficiency, train users for better adaptation, and improve performance, especially for low performers [10]. Studies also show that visual and audio signals can be combined to improve signal accuracy and user experience [11].

3. BCI Applications in Body Enhancement for Healthy Individuals

This section will explore specific BCI applications for enhancing human function, including the sixth finger, third arm, exoskeleton, and sensory feedback loop.

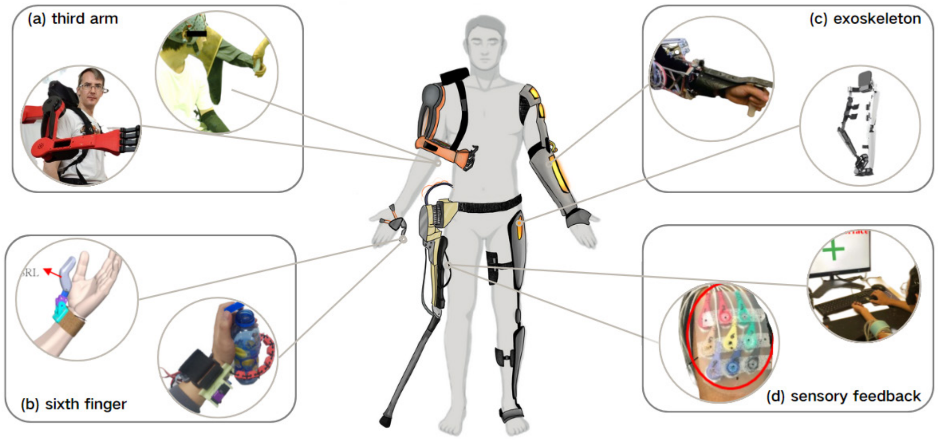

Fig.2 Illustration of BCI Enhancement Applications. (a) Supernumerary Arms: A robotic limb mounted on the body [12]. (b) Supernumerary fingers: A robotic finger attached to the hand [13]. (c) Exoskeletons: A hard covering that supports and protects human body [14,15]. (d) Sensory feedback loop system: A circuit using sensory information relayed back to the brain to refine movements [17].

The simplest way to enhance human physical capabilities is supernumerary robotic limbs (see Fig. 2(a)(b)). In one approach, researchers [13] introduced a novel EEG-EMG-based BCI for controlling a soft robotic “sixth finger.” This sixth finger enabled users to perform bimanual tasks using just one hand, such as opening the bottle, resulting in notable improvements in hand-thumb coordination. Additionally, a robotic arm controlled via MI was introduced [12]. Participants were able to control the robotic arm simply by imagining a grasping action. This setup allowed users to perform one task with the robotic arm, while simultaneously using their arms to do a different task. Exoskeletons for human enhancement have also been widely researched (see Fig. 2(c)). Researchers developed a brain-controlled lower limb exoskeleton using an MFCP-BLSTM model for motion imaging and gait planning [14]. It enhanced users’ walking ability through continuous control of the exoskeleton. In addition, another study designed an upper limb exoskeleton using a Gaussian mixture model to capture the natural motion characteristics of the human upper limb [15]. Their collision-free motion planning method, based on a human sensorimotor model, could enhance upper arm lifting abilities. Many augmented devices also require a feedback loop to transmit sensory data to the user (see Fig. 2(d)). Based on such ideas, researchers proposed an artificial sensory nerve pathway for SRLs to transmit fingertip pressure, and slippage information back to the brain [16]. Neurofeedback training has also been used for cognitive enhancement in healthy individuals. One study designed a real-time neurofeedback game using EEG [17]. They examined the setup’s ability to improve multiple cognitive skills, including overt and covert attention and working memory.

4. Transition from Therapeutic to Enhancement Applications

4.1 Inheritable Methods from Therapeutics

Therapeutic and enhancement processes share a similar workflow, both involving user and model training, signal acquisition, data processing, and application. For signal choices, EMG offers fast control, while EEG reduces fatigue. MI utilizing existing C3C4 motor imagery can directly establish a connection for the user, enabling control of the third arm model attached to the shoulder and neck through motor imagery alone. Consistent data processing and classification methods can be applied across applications. For therapeutic hardware, exoskeletons for stroke patients can be adapted for healthy users with minor adjustments to grip strength. Lightweight, energy-efficient devices from therapy can also be repurposed for portable human enhancement. Moreover, incorporating sensory stimulation into BCI systems could enhance performance by providing alternative feedback, reducing calibration time, and improving classification. This addition could advance BCI applications further.

4.2 Necessary Changes for Enhancement Applications

Some approaches in the medical field may face challenges during the transition, but with our suggested improvements, they can achieve more excellent value. On the input side, SSVEP is limited in daily use due to its reliance on large screens, though VR glasses might offer a solution. While requiring extensive training and lower accuracy, MI can improve speed when combined with other signals. On the output side, rehabilitation focuses on simple actions like gripping, while human enhancement requires more diverse input commands and better hardware. Battery life is a concern, as current prosthetics last about three hours, which is insufficient for enhancement. Energy-efficient designs and optimized battery placement could help extend battery life.

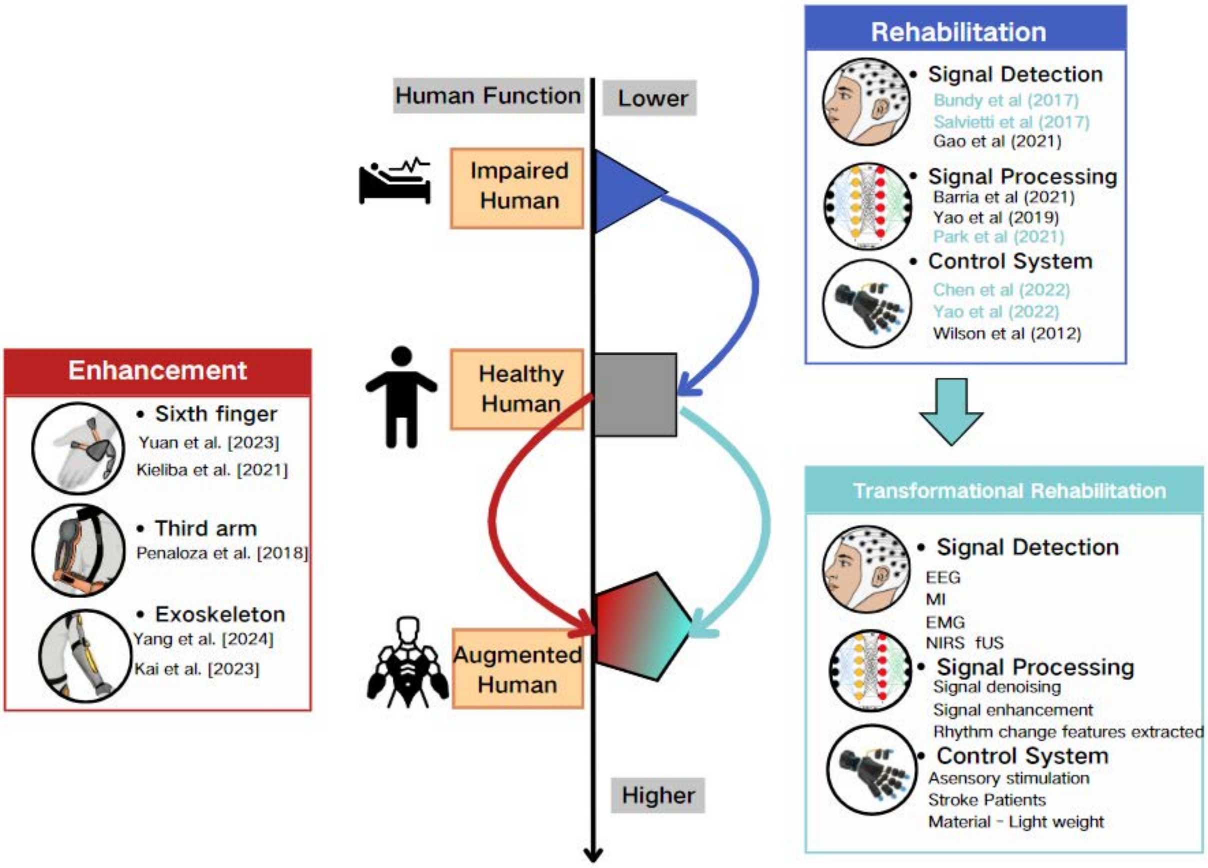

Fig.3 The article's structure outline.

Blue arrows represent literature on patient rehabilitation, while red arrows indicate methods for human enhancement in healthy individuals. Our work, shown in light blue, filters and adapts the deep blue rehabilitation literature to develop technologies with the same enhancement capabilities as those highlighted by the red arrows (see Fig.1).

5. Conclusion

Despite growing interest in BCI technologies for human enhancement, their practical application still needs improvement. These systems require better portability, functionality, and user adaptability. Safety concerns, such as reliable interpretation of user intentions and preventing side effects, must also be addressed. Ethical issues like informed consent, privacy, fairness, and accessibility are also crucial. Future development will focus on lighter, more efficient hardware and AI integration for faster responses. Overall, the transition of BCI technology from therapeutic to enhancement opens new possibilities, extending its applications and improving quality of life.

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Feiyue Xu, Xinyan Xu, Siyue Zhu, Ran Wei and Yubingjie Long contributed equally to this work and should be considered co-first authors.

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