**Brain-Computer Interface and Haptic Feedback**

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**Abstract**

The combination of Brain-Computer Interface (BCI) and Haptic Feedback (HF) systems represents a significant technological advancement in human-computer interaction and rehabilitation technologies. This project examined the concepts, architecture, and usage of the two components both separately and in combination. BCIs provide the means to facilitate direct communication from brain to external devices and enable bypassing the traditional muscular systems used by humans to relay commands and communication to a computer. Studies were completed on production methods of acquiring BCI signals, including EeEG, MEG, and ECoG, methods of understanding BCI signals such as preprocessing, feature extraction, and classification methods. While studying BCI, HF technologies were studied with a keen interest in the many types of feedback including kinesthetic feedback systems (Mechanoreceptors) or cutaneous feedback systems (e.g. influencers of touch which provoke a sensation), while exploring new paradigms of the rich sensations which HF systems can create, special efforts were made to research medical and rehabilitation application of the HF technologies (e.g. neuroprosthetics or surgical simulators). The project then focused on how BCI signals can control specific HF devices in real time. As such it discussed the key barriers related to controlling HF and BCIs simultaneously including issues related to latency, signal noise, and mapping strategies including control technique development. Several case studies are described in the area of assistive communication and mental health monitoring. The study concludes that the introduction of BCIs with HF systems can improve the quality of life for individuals with disabilities and introduce new possibilities for human-machine communication through immersive engagement. Future work may involve building more effective real-time models and increasing the adaptability of these systems for broader applications.

**1. Introduction**

Current technologies such as haptic feedback (HF) and brain-computer interfaces (BCI) have garnered a lot of interest in the last decade particularly because of BCIs capabilities that allow humans to operate computers or other man-made systems with the direct neural impulses they send to the BCI device. While BCIs allow a person to manipulate a device through brain impulses, haptic feedback enhances the sensory experience by allowing the user to receive information through tactile sensations.

For some time, scientists and academics interested in direct human-computer connection, have been purposely trying to correlate the functions of the human brain with external environments. However, with the advent of the Brain-Computer Interface (BCI) system, the human brain and former environments are now highly intermixed. A Brain-Computer Interface is a brain-machine interface which communicates with outside changing environments in real-time. The Brain-Computer Interface system utilizes specific signals at various frequencies from the user’s brain activity to communicate to the computer and convert to the desired response from the user. This allows users to exercise brain activity on an external device, regardless of being controlled through muscles or peripheral nerves. [1]

From basic EEG recording, the development of BCI systems has progressed to incredibly effective brain-computer communication.

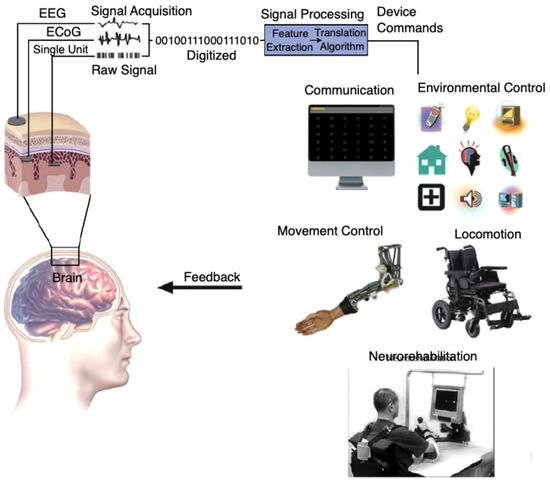


Figure 1 Development of BCI System

Haptics is the use of touch to convey information. These days, haptics are becoming common across many devices to provide information, especially using vibration to alert the user to new information.[2] Haptic Feedback (HF) is a naturalized use of touch and hooking in to touch to provide information or augment the user experience. HF contributes to the increase of touch with tactile, force and temperature feedback across different domains of human use. HF is increasingly important in a range of applications, including virtual reality, robotics, and rehabilitation.

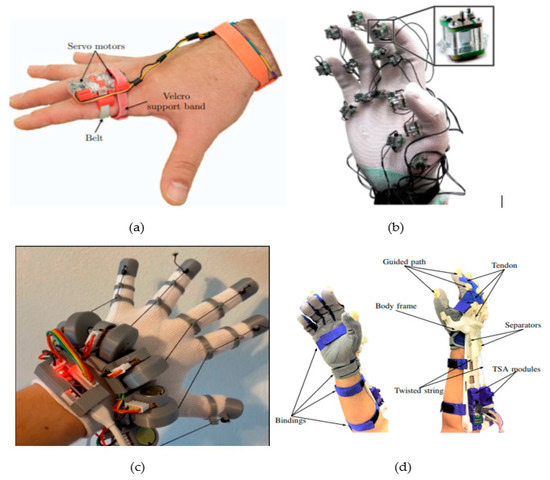


Figure 2 BCI and HF Combination

The combination of BCI and HF is developing rapidly in different domains, particularly in improving assistive technologies. The integration of BCI and HF, particularly as it relates to enhancing various prosthetics or rehabilitation devices, is particularly significant for those individuals who have mobility impairments. By incorporating brain signals with tactile sensations, users have access to more intuitive potential control over artificial limbs and a greater sense of embodiment. In the context of virtual and augmented reality (VR/AR), BCI and HF integration has the potential to provide even more immersive and interactive experiences. In this context, a user may be able to navigate through a virtual environment with their thoughts while receiving realistic tactile sensations, essentially merging the digital and physical worlds.

Healthcare is at the very beginning of an exciting journey with haptic technology. First, haptics has brought about new ways to teach clinical skill acquisition with surgical simulators that include suturing simulators, periodontal or dental implant simulators, and sensate shadow hands. Haptics has shown promising outcomes for supportive work in clinical practice with things like interventional radiology treatments, along with the remote surgery that uses haptic input and the way of perceiving it, conducting a prescribed medical operation. Haptic devices have also been shown to enhance patient and clinician engagement with medical devices when paired with other technologies such as virtual reality and artificial intelligence.[3]

Human augmentation and assistive devices are another area for BCI and HF integration. Wearable devices could also enhance cognitive abilities or offer sensory augmentation; haptic feedback could offer another way to input information. If you think about individuals with sensory impairments, this technology could provide them with new ways of perceiving and interacting with our world.

As the research field continues to grow, we expect to see an even more integrated BCI and HF technology which will drastically change our interactions, human option capabilities, and life opportunities for people with disabilities.

**2. Brain Computer Interface (BCI)**

2.1. History Of BCI

BCIs first appeared in the 1970's. BCI researchers are pursuing this ambitious and challenging project not only because they hope to develop a new output channel for patients with significant disability, but also because they want to continue the evolution of human direct control of external systems. At that point, it was done using animal studies for establishing a direct communication bridge between the brain and the outside world.

In addition, two landmark studies showed a BCI system recovered an arm from paralysis by using the system as the treatment for neuropathy. The efficacy of the intracortical BCI system for rehabilitation of neurologic limb problems was demonstrated by Ajiboye et al. [4]

2.2. Structure Of BCI

The BCI system employs a closed-loop system. In a closed-loop system, feedback is given for every action the user performs. For example, for a robotic arm to be controlled by a command based on an imagined motion of a hand. This arm's basic mobility requires a multitude of internal activities. The process begins with our brains, which are one of the largest and most complex organs in our body and consist of multiple billions of nerves and connections of billions of synapses to share information. Figure 2 demonstrates the process of turning signals from the human brain into an actionable command and is described in more detail below.[5]

2.3. Types Of BCI

Invasive methodologies are probably the most modern, most widely used approaches and will be explained in the next section, because the objective of this research project is to focus specifically on BCI research and development. There are three more recognizable approaches to BCI, established also based on level of invasiveness. The following section will overview and summarize these three approaches.

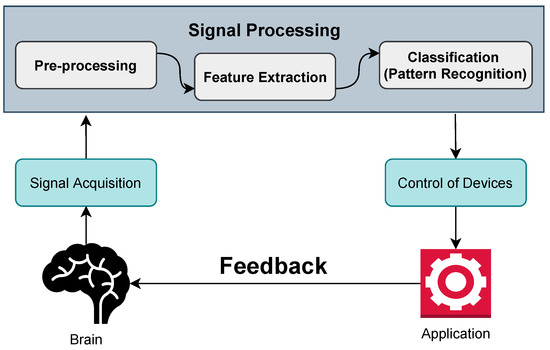


Figure 3 Process of turning signals from human brain into an actionable command

1. Invasive BCI

Invasive machine-brain interfaces involve the surgical implantation of electrodes directly into brain tissue. One notable situation is a quadriplegic individual who has suffered a spinal cord injury from a car accident. This injury severed the connection for motor-related neural signals between the person's brain and body, whereby any activity by the individual's limbs is gone. To restore this person a degree of mobility, surgeons implanted microelectrode arrays in the motor cortex of the individual. The microelectrode arrays record the neural activity related to the person's intention to move their limbs. This data is sent to an external decoder that interprets that neural activity into motor commands to operate either a robotic arm or an exoskeleton. The quadriplegic individual is trained to learn how to move the robotic device simply by thinking about the hand and trying to execute a task with the device. Invasive approaches offer high-resolution, correlated signals that allow for very fine motor control based on the decoded signals and provide real-time feedback to the user as they learn to be skilled with the device. That being said, there are significant risks for the individual, such as infection, damage to brain tissue, or degradation of signals due to scarring as implantable devices are used over long timeframes. Nevertheless, invasive brain computer interfaces are an important component of neuroscience research and the restoration of functions that have been lost due to disability in individuals. Many companies, such as Neuralink, are facilitating the development of invasive BCI technology toward other uses, like controlling digital interfaces or restoring sensory inputs (e.g., vestibular). Invasive BCI's high fidelity approach to signals has potential for fine control tasks; however, ethical and medical concerns and difficulties must be addressed before they are used in clinical practice.

1. Non-invasive BCI

Non-invasive BCIs do not utilize any surgical interventions compared to the invasive types. Non-invasive BCIs typically employ sensors worn externally located on the scalp. An example of a non-invasive BCI would be EEG headbands. Suppose in a classroom, students wear smart EEG headbands that monitor brainwave activity. This usage allows for the measurement of attention levels. If the BCI noted distraction related to a decrease in beta wave activity, it could provide feedback to the student through a vibration or visual cue. This would instruct the student to refocus. The teacher would see analytics and indications of attention in real-time for the whole class to alter the teaching method. This example describes how non-invasive BCIs applicable to supporting improvements in cognitive performance by healthy people pose no health risk. It is easy to wear, portable, and low-cost. These characteristics of non-invasive BCI make them appropriate for educational, gaming, and wellness uses. Non-invasive brain-computer interfaces (BCIs) have the main disadvantage of lower spatial resolution compared to invasive approaches, and a greater chance for noise and artifacts. Despite the limitations, and not yet commonly found in everyday life, non-invasive BCIs have become popular because they are safe, adaptable, and readily accessible as technology improves. They will provide an accessible means to support improvements in cognition that we consume without clinical intervention to monitor mental states like fatigue, stress, or engagement. In time, we will see everyday technology infused with cognitive augmentation through non-invasive BCIs without requiring medical intervention.

1. Partially Invasive BCI

Partially invasive BCIs are characterized by using an implantable device that is located inside the skull, but outside of brain tissue, such as on the surface of the cortex. As an example, a patient with locked-in syndrome is completely paralyzed but is fully aware. Given their lack of movement or speech, they are truly “locked-in.” Under normal circumstances, a patient would have no means of communication, making any meaningful interaction almost impossible for this patient. To address this issue, a primary consideration is to implant a partially invasive BCI like an electrocorticography (ECoG) system in their skull. ECoG records electrical activity from the cerebral cortex of the patient with higher quality than any non-invasive systems and does not penetrate the brain tissue. When using a BCI in this scenario, the intention is for the BCI to decode the neural patterns associated with imaginable speech or motor imagery and transcribe it into text or synthesized voice. Ultimately, the patient could communicate basic needs, respond to questions, and express emotionality in their communication. Partially invasive systems offer higher signal quality than non-invasive systems but pose lower risk to the patient than implanted systems. There are still surgical processes and risks involved with partially invasive BCIs, but the ECoG represents a good solution to provide the patient with long-term communication assistance while attempting to balance signal quality and risk. Research is ongoing into developing wireless versions of these systems and creating more user-friendly systems. Lastly, partially invasive BCIs provide the opportunity to safely provide high-quality experience for patients that require high performance BCIs but are not appropriate candidates for direct brain implants via invasive surgical procedures.

2.4. Data Processing & Interpretation in Brain-Computer Interfaces (BCIs)

2.4.1. Signal Acquisition

Different sensing modalities obtain brain signals with different trade-offs:

EEG (Electroencephalography): Non-invasive use of scalp electrodes to measure ultimate voltage fluctuations occurring on the cortical surface. EEG is temporally accurate (~milliseconds) and pragmatically inaccurate with spatial allocation (~centimeters) . It is inexpensive and practical, but suffers from external artifacts, possible nuisance variability and environmental disturbances.

ECoG (Electrocorticography): Invasive method that enlarges electrodes placed on the cortical surface (during surgery) from which the ultimate local field potentials can then be streamed.ECoG can reach great spatial (<1 mm) and temporal fidelity with excellent signal-to-noise ratios, providing more accurate neural signals than EEG.

fNIRS (Functional Near Infrared Spectroscopy): Non-invasive optical method obtaining measurements of blood oxygenation changes occurring in the cortex. It spatially provides moderate location accuracy (few millimeters) while lacking temporary accuracy (~ seconds). While fNIRS can provide better electrical noise immunity than EEG, it can't assess electrical brain activity directly.

MEG (Magnetoencephalography): MEG (Magnetoencephalography) employs magnetometers to non-invasively measure magnetic fields generated by neural activity currents. MEG is spatially and temporally more precise than EEG. MEG usually has better spatial resolution than EEG. However, due to the requirement of expensive shielding apparatus, it is mainly used in research labs.

Each modality makes tradeoffs with respect to invasiveness, signal quality, and feasibility. In practice, most BCI systems will utilize non-invasive EEG or fNIRS (often as part of hybrid systems) while MEG/ECoG are engaged in specialized laboratory or clinical environments.

2.4.2. Preprocessing Techniques

Raw neural recordings contain many different artifacts and noise that should be removed or reduced. Artifacts are categorized as either:

* Environmental or hardware noise: e.g. power-line noise (50/60 Hz), amplifier noise or fluctuations, electrode drift, etc.
* Physiological artifacts: e.g., eye blinks/movements, cardiac (ECG) signals, muscle (EMG) and scalp muscle activity that can overlap the EEG frequency bands.

Preprocessing methods can help deal with these artifacts. Typical methods include band-pass filtering (to isolate EEG frequency bands) and notch filtering (to remove line noise) as well as spatial filtering or blind-source separation. For instance, ICA can decompose the EEG into independent components, allowing to identify and reject the components that may be associated with artifacts. Other methods (e.g. wavelet denoising; regression against reference channels, etc.) aim for the same clean EEG result that neural features dominate. It is often necessary to remove or clean artifacts in order to achieve better signal quality prior to interpretation.

2.4.3. Feature Extraction

Cleaned EEG signals become compact feature vectors used for classification. Important extraction procedures are:

* Fourier/Spectral Analysis: The signal is transferred to the frequency domain, featuring its power in the canonical EEG bands (delta, theta, alpha, beta, etc.). The researchers will implement the Fast Fourier Transform (FFT) or a power spectral density to produce features like band power or spectral peak magnitudes. The spectral features represent oscillatory patterns that are dominant, possibly useful for delineating mental states.
* Wavelet Transform: Wavelets give a time-frequency decomposition that preserves transient, non-stationary structure. Projecting EEG to wavelet bases at multiple scales produces coefficients that localize in time and frequency. Its multi-resolution approach is good for detecting fleeting events (e.g., event-related potentials or bursts of oscillations) that might get lost in a fixed-window Fourier Transform, or if temporal events are of importance. Wavelet-based features often enhance classification results because they use frequency information alongside temporal information.
* Principal Component Analysis (PCA): PCA takes multichannel EEG and projects it into a new orthogonal basis, where the basis vectors are the principal components. The first several principal components explain most of the variance, so it is effective to retain the first components, collectively making a data compression. By ignoring the low-variance components, PCA decreases the dimensionality/ noise of the data. The principal-component scores for the original observations form a new feature bank that is, in essence, a vector representation of the underlying brain activity. All these feature transforms turn sample series (e.g. waveforms), into so-called vectors (e.g. spectral amplitudes, wavelet coefficients, PCA scores), which encodes task-relevant, neural information about the activity in the cortical areas, vastly simplifying data for classification.

2.4.4. Classification Algorithms

The characteristics obtained will then feed into classifiers that will decode the user's intent. The most common models include:

* Support Vector Machine (SVM): a classical supervised classifier that will find the optimal separating hyperplane in feature space. In the context of BCI, SVMs are commonly used to run on spectral or spatial features (i.e. motor imagery band power) on a two-class task basis. SVMs perform well on moderate-sized datasets and seek to maximize the margin, which tends to improve generalization.
* Convolutional Neural Network (CNN): A deep learning model that can learn hierarchical spatial–temporal features autonomously. CNNs can take raw EEG or EEG time-frequency input (which are often structured as 'images' of channels vs time/frequency). CNNs have also dramatically improved decoding accuracy in recent studies in the context of BCI. For instance, CNNs can learn to separate P300 patterns or motor imagery rhythm patterns without any manual feature engineering. They will excel if there are large, labeled datasets to learn from because they can learn complex discriminative patterns from the data.
* Recurrent Neural Network (RNN/LSTM): An RNN (especially Long Short-Term Memory networks) can be thought of as specifically designed for sequential data. LSTM cells (often used within RNNs) have memory gates that explicitly model dependencies over time. RNNs can represent time-varying activities in EEG data, such as the time-varying waveform of an event-related potential or other patterns that occur over time. In practice, RNN and CNN layers are often combined (e.g., CNN–LSTM architectures) to incorporate spatial filtering and to take account of temporal context.

Each classifier is trained on labelled EEG features to output predictions to inform understandings of commands or brain states. In general, simplicity is valuable; computationally simple models (e.g., support vector machines or linear discriminant analyses) can efficiently learn from EEG data from small datasets, while complex deep networks (e.g., CNN/RNN) may allow for richer feature learning and require larger datasets and tuning. Together these algorithms parse the processed brain signals into an actionable output, marking the conclusion of the BCI signal processing pipeline.

**3. HAPTIC FEEDBACK (HF)**

3.1. Introduction

Haptic feedback is a technology that reproduces the sense of touch by applying mechanical forces, vibrations, or motions to the user. Vibrations that a smartphone gives off for notifications or the rumble you feel when using a game controller are common examples of haptics. Haptic feedback sends tactile signals to the user and anchors a virtual experience by making it more tangible. Haptic systems usually consist of sensors, actuators, and a control unit. When users engage with the haptic device (e.g., tapping a touch screen or manipulating a joystick), the sensors detect the interaction and send signals to the controller, which then activates the actuators (for example, small motors or linkages) to react to the sensation of touch. For example, a phone's vibrating motor can turn on and buzz at different intensities to simulate the sensation of pressing a button or an alert.

3.2. Types of HF

Haptic feedback systems can generally be classified into two main classifications characterized by the type of feedback they provide: cutaneous feedback, and kinesthetic feedback. Figure 5 shows a few different cutaneous feedback and kinesthetic feedback devices that are currently being developed. Kinesthetic feedback devices and cutaneous feedback devices both have their differences and values to haptics and understanding the strengths and limitations of each feedback will help create new technologies.[2]

1. Kinesthic Feedback

The majority of kinesthetic feedback devices make use of actuators generally mounted to either a hand or an arm that track movement and provide an appropriate force to that movement to allow or restrict movement and replicate certain types of motion such as gripping and lifting of objects. Unlike cutaneous or tactile feedback systems which have actuators that can directly stimulate mechanoreceptors, for example with electrotactile or temperature-based haptic feedback, kinesthetic feedback systems use mainly force feedback, which generally requires using typically large actuators to create sufficient forces to the user. Kinesthetic feedback can be classified into two categories, grounded and exoskeleton. Grounded force feedback systems are described as feedback systems that have a stationary platform, and the user attached to or holding an end effector (a manipulator or controller) while that end effector is tracking the user's position with the ability to modulate the amount of force that is applied. Exoskeleton-based feedback systems apply actuators that are mounted onto and/or attached to the user's arms and/or hands and are ungrounded.

Several different actuators have been used over the developmental course of kinesthetic feedback systems. Early kinesthetic feedback systems used hydraulic cylinders connected to exoskeletons placed on the arms. However, the weight and bulkiness of hydraulic systems limited their application outside of an experimental lab. After hydraulic actuators, pneumatic actuators began to see wider application in kinesthetic feedback systems due to their lightweight design which permitted less bulky and less constricting suits; however, use of pneumatic actuators is still limited by the requirement of a source of pressurized fluid. The advancement of technology to miniaturize actuators has ultimately led to lighter and smaller kinesthetic feedback systems and better form factors when placed on the hand. Both Dexmo and Maestro use several motors with either moving end effectors or synthetic fiber, respectively, that are used as their braking system [95,101]. Cable-based actuators are also becoming increasingly popular as they tend to be lightweight, and the adaptable cable design of cable-based actuators allows motors to be placed more freely without interfering with the natural movement of the hand.

2. Cutaneous Feedback

The separation of the actuator and the location of feedback can benefit cutaneous feedback devices. Unlike kinesthetic feedback systems that usually require larger actuators since they must be attached to the hands, arms, or both, cutaneous feedback systems can only be applied in the key locations of the hand, usually where the mechanoreceptors are most densely populated, and obtain sufficient feedback. The more concentrated nature of cutaneous feedback allows for far smaller devices to be developed while providing far less force while still being believable. This has led to several different solutions to reproduce touch.[2]

2.1. Vibrotactile Simulation

Vibrotactile stimulation is the most common type of cutaneous feedback used; it is inexpensive, low-power, low-profile, and can be attached to a range of locations on the hand. Many electronic devices including phones and computers include vibration patterns to alert individuals and most commercially driven virtual reality systems (e.g. Oculus Quest, HTC Vive etc.) involve some form of vibrotactile stimulation as their main source of cutaneous feedback. Vibrotactile phantom stimulation is used to provide slippage and weight illusions on objects based on a series of magnetic pins that vibrate in response to the individual interacting in the virtual system. As the phenomenon of human texture recognition occurs with micro vibrations in the range of 1 Hz to approximately 500 Hz, the potential exists to mimic these micro vibrations with small actuators to provide finger-mimicking movements and produce haptic feedback.

2.2. Skin Indentation

Skin Indentation is another form of cutaneous stimulation which is very common for applications of this nature. It relies on the use of actuators that can apply a normal force onto the skin by way of indentation and can be used to potentially project the weight and shape of an object depending on the application. They are almost always fixed onto the skin or glove. Although most of the devices are attached to the fingers which have the greatest density of receptors, they can also be attached to the skin or glove and are often considered default locations for attachment. Depending on the amount of force applied, one can scale the perceived amount of force applied on a virtual object whether inadvertently or on purpose. The most common form of motor for implementation of indentation-based feedback uses motors to drive a series of end effectors directly onto the skin and at various forces. Even though skin indentation is a cheap, effective method of simulating touch, it suffers from bulk issues as the actuators which drive the system need to sit at the fingertips and can restrict an individual's movements which is a non-issue in virtual environments but an important factor to consider in augmented reality systems in which interaction with both virtual systems and the real-world systems may be required.

3.3. Haptic Feedback in Medical Devices

Haptic devices are important in medical applications because in many situations, tactile cues are important. Surgeons often need to feel the resistance of tissue when cutting. Supine therapists often use touch to guide or direct a patient. And prosthetic users often rely on feedback from haptic devices to be able to control their prosthetic. The idea is that allowing users to have the experiences of touch through haptics will lead to more effective training, practice, and ultimately improved patient care. For example, surgical trainees who are training with a haptic simulator may be able to feel the difference between healthy and unhealthy tissue in a virtual environment.

3.3.1. Surgical Simulation and Training Devices

Virtual surgical simulators often include haptic interfaces that mimic real instruments. Trainees use force-feedback handles or styluses in a 3D environment, feeling resistance when the virtual tool contacts tissue. For instance, laparoscopic training systems provide handles that push back when touching organs. Commercial devices like the LAP Mentor or dV-Trainer offer modules for procedures such as suturing, with touch-based feedback. Studies have shown that trainees learn faster when simulators supply realistic force cues alongside visual feedback.

3.3.2. Rehabilitation and Therapy Haptic Devices

In the rehabilitative context, haptic technology is manifested in robotic rehabilitation and interactive rehabilitation exercise devices. External robotic arms, or haptic gloves can facilitate patient movement through the externally applied forces and vibrations during the rehabilitation exercise. An example of this would be an upper-limb rehabilitation robot which supports a patient’s arm and alters the resistance value as the patient reaches a target and provides an environmental push or pull. Haptic gloves would include vibrating or force-resistive elements that would provide stimulation to fingers during hand rehab exercises, to help individuals with strokes regain dexterity. The provision of sensory cues in rehab may increase engagement in the rehabilitation process and potentially improve motor recovery.

3.3.3. Prosthetic Haptic Systems

Haptic feedback systems in prosthetics provide a user with a sensation of touch in their artificial limb. Many prosthetic hands and feet use sensors (for pressure or movement) and the actuators are perceived at the user's body. For instance, a prosthetic hand connects fingertip sensors to small vibrating motors located on the upper arm; when the hand closes on an object, the motors would buzz, indicating how much grip effort is being placed on the object. Some extremely advanced systems use electrodes implanted on nerves to provide a realistic sense of touch feeling by activating the nerves directly.

3.3.4. Wearable Haptic Medical Devices

Wearable haptic devices are worn on the body to provide feedback in daily life and therapy. Examples of wearable haptic devices include belts, vests and gloves that have vibrating actuators. To give an example, a posture-correcting device, such as a belt, can vibrate or provide feedback to a user when the subject has slouched. In balance training, a shoe sensor could trigger a belt vibrating if the patient leans too far, prompting the patient to correct their position. Haptic gloves or sleeves can also provide guidance for arm and hand exercises with vibrations or resistance.

**4. INTEGRATING BCI WITH HF**

4.1. Integration

Neural signals are recorded, analyzed and processed in the moment. Signals are pre-processed and filtered (band-pass, notch) to remove noise artifacts and then segmented into smaller analysis windows.

* Signal Acquisition and Preprocessing: Sensors recording neural brainwave information filter and suppress artifacts to improve the quality of the neural signal.
* Feature Extraction: Neural features (e.g. band power, ERP amplitudes, etc.) describe brain state from each respective window.
* Classification/Decoding: The features are passed into classifying models that map features to discrete control commands or continuous outputs.

Decoded commands are immediately sent to the haptic device through a low-latency link (e.g., Bluetooth LE or Wi-Fi). The BCI processor (potentially in a headset or connected module) composes compact control packets (e.g., a byte denoting, for example, vibration intensity) that it transmits to the actuator. The communication protocol must minimize delay and maximize reliability.

The user is generating the commands to the haptic device from their brain and the haptic device is providing tactile feedback back to the user, which creates additional neural signals. For example, imagining a grasp may close a robotic gripper, while at the same time, the user is receiving a brief vibration as tactile feedback. The user perceives the tactile cue and refines mental commands which closes the sensorimotor loop and improves and haptic control over time.

4.2. Communication between Brain Signals and Haptic Devices

Brain-to-device mapping takes decoded neural output and provides an appropriate haptic action. Discrete mappings make a discrete mapping between the detected intent to a specific feedback pattern, whereas continuous mappings take a neural measure and convert to actuator intensity. In multi-DOF control, two different features of the brain could modulate two different actuators (e.g., one channel modulates left-right movement, while another channel modulates up-down motion).

* Discrete Mapping- Each decoded state is mapped to a specific haptic output (e.g., imagining movement of the left hand produces a left-side vibration).
* Continuous Mapping- A neural metric (like band power) is scaled to a corresponding haptic parameter (like vibration amplitude).
* Multidimensional Mapping- Different neural signals are used to drive each actuator in multi-DOF interfaces.

Adaptive feedback loops improve stability. The system can modify its decoding model online (co-adaptation) as it tracks changes in signal, and it can adjust haptic output in real time. Both feedback strength may increase if signals from the user weaken. This two-way adaptation enables the user to maintain stable control.

Calibration creates a personalized controlling mechanism. In this case, a user must perform known mental tasks during the calibration phase while the system acquires EEG data. The acquired data are used to train the classifier or mapping function. Calibration can also configure user-specific parameters (as an example: comfortable level of vibration). Another option to accommodate the user for previous task-based sequence would be through transfer learning or recalibrating periodically to lessen the setup stage.

4.3. Challenges in real-time executions

Latency: EEG processing windows (in the hundreds of ms), and classification further add latency, and then wirelessly transmitting the EEG results introduces additional latency. A system can minimize latency by minimizing windows and finding efficiencies in computation to maintain overall loop delay within acceptable variance.

Noise and Artifacts: EEG is susceptible to noise (eye blinks, muscle movement, electrical interference) which introduces artifacts. The system can employ robust filtering and rejection of artifacts, but the nature of unpredictable noise will continue to have some impact on control. Additionally, one could consider using approaches like error-checks or multi-channel confirmation to reject spurious commands or erroneous results during the control process.

User Adaptation: Users will have to train to produce consistent neural patterns, often referred to as "brain patterns." After learning protocols (often in the form of games) users may be asked to produce a neural activity that closely resembles a neural motor component (such as a mental action) in association with what the feedback signifies. Adaptation to using a BCI-HF differs for everyone as external cues (such as haptic feedback) can speed up the process when relying on intuitive success, and there remains a time uncertainty for generating reliability of control.

Energy Consumption: Wearable BCI-HF systems consist of attached components that operate off batteries. Continuous sampling, or acquisition of EEG adds consumption with an additional power consumption to receive and process this EEG information wirelessly through communication protocols, while also providing haptic actuation output. Designers and engineers use low-power electronics and duty cycling (such as only sampling based on need, or BLE) to conserve power consumption. Efficient actuator drive and optimization practices relate to the likelihood of an acceptable battery life.

**5. APPLICATIONS**

BCIs have been proposed for a wide range of applications, namely, in medicine, neuroscience research, education/training, human-computer interaction, and even gaming/entertainment situations in which users control virtual objects purely by thinking with no movement at all. Outside of these traditional applications there are other investigations ongoing in new realms like thought-controlled wheelchairs, which would allow disabled individuals a greater level of mobile freedom without manual navigation; prosthetic devices giving amputees better manipulation control than ever; communication aides for people suffering from serious speech impairments; remote monitoring of vital signs without requiring patients to stay confined in a hospital; and other scenarios such as mind-controlled drones. We can only imagine the extent of possibilities in further understanding our brain, so let's look at few examples of how BCI technology is already advancing its use:

5.1. Neuroprosthetic

BCIs are involved in the development of neuroprosthetic devices, allowing people with mobility challenges to interact with external devices like wheelchairs and robotic arms using signals from their brain. For example, the BrainGate neural interface system is a more novel device that, when implanted in the brain, can record electrical activity from neurons and convert that activity into command for controlling external devices.The use of BCIs in neuroprosthetics is a rapidly growing field with a variety of applications, from enabling communication for those with lost communication ability because of injury or illess, to new and enhanced levels of control of prosthetic limb devices. Although BCI technology has been applied in a medical context for decades, only recently has it been explored more directly in the context of neuroprosthese.[6]

An application of BCI technology within neuroprosthetics is brain-controlled robotic arms and hands. These devices allow a user with spinal cord injuries or amputations to move their prosthetic limb using just thought and no manual action such as switches or joysticks. It can additionally serve as an assistive device for someone limited in movement, such as a stroke patient or someone with progression neuromuscular degeneration illness, for example, ALS (amyotrophic lateral sclerosis). Using the electrical signals produced by neurons in the user’s brain, these devices can effectively predict how to move in response to input from the user and potentially provide them with greater independence and freedom of movement.[6]

Another application of BCI technology within neuroprosthetics is for establishing communication in people who have lost the ability to speak due to paralysis from ALS, stroke, or traumatic brain injury. In this scenario, electrodes on the scalp are able to pick up electrical activity from the neurons that would normally create the capacity for producing speech and interpret that into words on a computerized voice synthesizer. This permits people who cannot produce sound physically to communicate their thoughts and feelings to a bit more freedom than writing those thoughts and feelings down or simply typing out messages with eye-tracking software programs.

Lastly, neural implants are another type of BCI technology that is being investigated in the field of neuroprosthetics research—especially in so-called "neurohybrid" systems, which also include biological components (nerves) along with artificial components (microprocessors). Neural implants involve direct implantation of electrodes directly into areas which control movement, so neurons can send muscle commands instead of relying on issuing external commands (IE: implant could send specific signals in response to direct neuronal activity enabling greater response time than previous BCI activity, which attempts to read discharges in neurons and then send signals constructed from that read back to muscle tissue through scalp electrodes).

Overall, BCI technology is an exciting new field with many possible applications in periprosthetic—from simply restoring our communicative abilities, to allowing us to have purposeful control of prosthetic arms and legs, and beyond. As the research and field continue to unfold, it is reasonable to assume that BCI technology will provide individuals who experience disabilities greater independence and mobility than they ever had.

5.2. Communications

BCI technology is also being utilized to develop new communication methods for those who have lost the ability to speak or write due to paralysis or other conditions. In recent years BCI technology has gained popularity in enabling communication between humans and machines. BCIs are devices that measure brain activity (e.g., electrical signals from the brain) and then take this information and utilize it to control external devices and or systems. BCIs are being used for a variety of applications, including the control of prosthetics, medical diagnostics, rehabilitation therapy, gaming, control of robotics, and communication. This kind of research is exciting and promising as it can be used for people with disabilities who can communicate verbally or even physically due to some degree of paralysis or other type of medical condition.

Other research has examined more advanced applications of BCI technology for communication, such as typing on a computer keyboard or issuing voice commands by means of voice recognition software. These types of applications can offer some individuals with multiple severely impaired motor control some regained independence when communicating with others. Moreover, there have been other attempts to build interfaces to allow users to produce language, solely in thought with EEG signal recordings. This technique is still in its infancy and requires further development before widespread use and application, but it represents a great opportunity for future uses of BCI technology in augmenting human-machine interaction.

Overall, BCI technology is capable of augmenting communication in a way that can be revolutionary for communication as a whole. Although there is a substantial amount of research and development to be conducted regarding this technology before it can be brought to general use and acceptance, the future of those with disabilities being able to communicate more independently and effectively with others or, in some cases, to actually create language in thoughtless terms are opportunities that should make all researchers in the field excited.

5.3. Mental Health

BCI might be helpful in mental health care in various ways, including the assessment of cognitive functions (ex. attention, memory), detecting changes in emotional state, tracking progress in therapy, measuring stress or relaxation, providing a feedback modality during biofeedback, diagnosing neurological disorders (ex. Alzheimer’s disease; Parkinson’s disease), improved motor function after stroke or TBI, helping people suffering from depression to manage their symptoms using self-regulation strategies, addressing public speaking anxiety, and more. Additionally, BCIs have also been posited as effective tools to help patients manage negative emotions (e.g. anger, fear) to develop better coping skills.

There is research that indicates BCI could potentially change how mental health care is administered because it could allow for early intervention before someone deals with more serious psychological problems. Research has indicated certain types of EEG-based BCIs might be able to detect physiological cues related to depressive distress that might be missed using other traditional assessment tools (i.e., questionnaires, clinical interviews, etc.).

**6. CONCLUSION AND FUTURE WORKS**

6.1 Conclusion

BCIs allow users to communicate intentions using neural signals instead of using standard controls, and haptic systems provide touch sensations, to incorporate realistic movement. Both BCIs and haptic systems would be powerful on their own: BCIs allow multiple pathways to reconnect communication, or get novel controls, and haptics introduce a level of physicality to virtual experiences. As systems, they connect in a bidirectional loop between the brain and device, which leads to possible improvements in naturalness and effectiveness of interactions. This mutual relationship is crucial for closed-loop applications: a user's brain signals control a device or action in a virtual environment, and then a real-time haptic response from the device gives inputs back to the user. This input supports learning and can also create precision. Such as a person who is imagining a movement to control a prosthetic arm, benefitting from the prosthesis that also provided an identical touch or level of force sensations, both allowing this person to imagine what he/she felt to be a natural movement, and increasing their motor learning speed. In immersive virtual reality, combining a BCI with haptics provides experiences that are richer, allowing that person to move the environment through thought instead of traditional channels and feel the virtual objects in a similar way as real objects.

Nevertheless, current BCI–haptic systems present serious drawbacks. Non-invasive BCIs typically provide noisy, low-bandwidth control signals with lengthy training time, while implanted BCIs involve surgery risks and long-term maintenance burdens. Haptic stimulators can be heavy or power-hungry devices that fail to even provide fully realistic touch or force. Incorporating two modalities increases potential pitfalls: delays in neural decoding or haptic actuation are damaging to the nature of the loop, and irrelevant or poorly aligned stimuli may confuse rather than help users. A great many prototypes remain within laboratories due to these technical and ergonomic limits. Attacking these problematic procedures will involve advances in multiple domains. Signal processing and machine learning can improve the ability to decode intent more consistently, while new materials or actuator designs offer lighter, less bulky, and more comfortable wearable haptic interfaces. Careful user-centered design will be crucial in providing the final combined interface as intuitive to use and non-fatiguing. With these advances, integrated BCI–haptic systems have the potential to present a more natural, rapid, and effective human–machine interface than either technology alone.

6.2. Future Scope Work

In the future, BCI-haptic systems will operate almost instantly and in a wearable opportunity. Computing, sensors, and miniaturization will provide wearers with almost instant decoding of the neural signal inputs and real-time delivery of haptic responses. Miniaturization will happen by way of small EEG sensors, thin implantable chips, and efficient processing chips that will remove weight and bulk from the BCI haptic devices. At the same time, the efficacy of the wearable haptic interfaces (for example, smart gloves, soft suits) will deliver full-body awareness without being cumbersome.

Artificial intelligence and adaptive algorithms will increase the potential of these work interfaces. Machine-learning models will familiarize the system with an individual person's brain patterns as they develop over time thereby improving accuracy and eliminating additional training. The AI will also optimize the quality of the haptic outputs by varying the strength of feedback response and monitoring the user's cognitive load or task-based environment as a context. In the future, BCI-haptic systems as interfaces should be able to learn continuously from multiple uses to automatically tune themselves for a more natural handling or assistance of the individual.

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