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Assistive Care BCI for Locked-In Pediatric Patient

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Approval

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Abstract

This feasibility report presents the development of a non-invasive Brain-Computer Interface (BCI) system tailored for a pediatric patient with Locked-In Syndrome (LIS) resulting from a spinal cord infection, leading to lower body paralysis and ventilator dependency. Despite intact cognitive abilities, the child has ceased verbal communication and lost interest in daily activities, necessitating a tool to restore autonomy and engagement through interactions with video games, cartoons, and toys.

The literature review reveals a significant research gap in pediatric specific BCIs, with limited child-friendly paradigms and challenges like data variability and training complexity. The proposed methodology integrates Steady-State Visually Evoked Potentials (SSVEP), P300, and Motor Imagery (MI) EEG techniques, supported by a custom dry-electrode headset, ADS1299 amplifier for signal conditioning, and advanced preprocessing (e.g., wavelet transform and ICA for artifact mitigation). Feature extraction employs methods like Canonical Correlation Analysis and Common Spatial Patterns, with classification via CNN or Transformer models, fine-tuned on datasets and personalized sessions. The user interface features SSVEP driven menus with reward loops for sustained motivation.

Feasibility analysis confirms technical viability using commercial components, with mitigated risks including signal noise (via adaptive filtering) and headset discomfort (through ergonomic design). The project promises immediate quality of life improvements for the patient and broader contributions to pediatric neurotechnology, affirming its potential for clinical adoption and global impact.

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Chapter 1

Introduction

This project focuses on developing an assistive care Brain–Computer Interface (BCI) for a boy suffering from Locked in Syndrome (LIS) due to a spinal cord infection. The patient's condition has rendered him paralyzed in his lower body and diaphragm, making him fully ventilator dependent. Crucially, he has no intellectual disability and was previously talkative and playful, even in the ICU. However, he has stopped speaking and lost interest in life after a period of time. This project aims to address his severe limitations in interaction and development caused by his inability to move or speak.

1.1 Motivation

The primary motivation behind this project is to provide a gateway to the world for this child with LIS. Despite his paralysis, he shows emotional responses to his favorite video games and displays interest in food, cartoons, and toys. Doctors believe that "he needs a reason to engage".

1.2 Problem Statement

The challenge is to design a non invasive, child friendly Brain Computer Interface (BCI) system that allows a pediatric patient with Locked in Syndrome resulting from a spinal cord infection causing acute flaccid myelitis, paralysis of the lower body and diaphragm, and full ventilator dependency to control assistive devices. Despite having no intellectual disability and previously being talkative and playful even in the ICU, he has stopped speaking and lost interest in life since December. This system aims to enable him to play video games, interact with stimuli like food, cartoons, and toys to which he still responds emotionally, restore a sense of autonomy, and enhance his daily life and well being, providing the "reason to engage" as believed by his doctors. A summary of the core problem, its impact, and the goal of this project is as follows:

- **Problem:** A pediatric patient with Locked in Syndrome (LIS), paralyzed but cognitively intact
- **Impact:** Unable to move or speak, limiting interaction and development
- **Goal:** Design a child friendly BCI system to restore sense of autonomy

Chapter 2

Literature Review

2.1 Research Groups and Child Centric Paradigms

The landscape of BCI research for pediatric applications involves several key research groups, each contributing unique insights and methodologies. Table 2.1 summarizes these groups along with their primary contributions and suitability for pediatric applications.

Table 2.1: Representative research groups/labs and pediatric suitability

Research Group/Lab	**Key contribution / focus**	**Pediatric suitability**
Jadavji et al. (U. Calgary)	Clinical BCI programs for kids using play as a motivator	High
Wadsworth Center (NY)	P300/BCI speller development	Moderate
U. of Tübingen (Germany)	Work with LIS patients	Low (adult focused, some invasive)
Wyss Center (Geneva)	Implantable BCI technology	Low (invasive; adult)
TU Graz (Austria)	BCI for game control	High (includes child friendly paradigms)
Kirton, A. (U. Calgary)	Ethics: BCI for children as a moral imperative	High

Research by Jadavji et al. emphasizes clinical BCI programs for children centered around play as a primary motivator [3]. Their work stands out. Empirical studies show that typically developing school aged children achieve BCI control quickly, with key findings indicating that visual imagery strategies outperform sensorimotor approaches in tasks like moving a cursor or controlling a remote car [4,5]. Furthermore, their work establishes functional outcomes using tools like the Canadian Occupational Performance Measure (COPM) and Goal Attainment Scaling (GAS), providing validated clinical benchmarks for measuring restored independence and goal achievement [6]. This evidence base is crucial for demonstrating that BCIs can deliver meaningful improvements in children's daily lives.

The work originating from TU Graz, focusing on BCI for game control, is highly relevant as shown in Table 2.1 [3]. Their emphasis is on self paced, robust BCI systems, essential for real world application. Real world deployment requires high information transfer rates (ITR), robustness against noise, and on demand operability [7]. The experience gained in developing computer game like applications provides a template for integrating BCI commands into the patient's favorite stimuli [8], making the technology more engaging and effective for children.

The Wadsworth Center's long standing contribution to P300 development is significant [3, 9]. Recent research addresses the unique challenges of training children with P300 based Augmentative and Alternative Communication (AAC) systems. Their findings identify key strategies such as scaffolding, gamification, clear verbal instructions, and immediate biofeedback to manage the typical challenges associated with pediatric attention span variability and cognitive load [10]. These protocols are vital for the proposed User Interface design, ensuring that children can engage with the system effectively despite their developmental limitations.

In contrast, the decision to develop a non invasive BCI is mandatory due to ethical and developmental considerations. Adult focused invasive systems, such as the implantable BCI technology developed by the Wyss Center or the Utah Array from Blackrock Neurotech, are deemed low suitability for this pediatric application as indicated in Table 2.1 [3, 11, 12]. The Utah Array involves significant surgical risk, justifying its exclusion for a first line assistive care system [12]. The risks simply outweigh the benefits when dealing with vulnerable pediatric patients. Similarly, the University of Tübingen's work, while essential for Locked In Syndrome (LIS) patients, often involves adult subjects and some invasive techniques, further justifying the focus on non invasive electroencephalography (EEG) [2, 3, 13].

2.2 Commercial BCI Systems

A review of commercial devices, presented in Table 2.2, demonstrates that viable building blocks for a customized system exist [3]. These commercial platforms offer a starting point, though most require significant adaptation for pediatric use.

Table 2.2: Commercial/noninvasive devices and pediatric suitability

Device/Company	**Non invasive**	**Suitability for pediatric use**
g.tec medical engineering	Yes	High (markets systems for children)
Blackrock Neurotech	No	Low (invasive; adults)
NeuroSky	Yes	High (accessible; game integrations)
ANT Neuro	Yes	Moderate (may need customization)
OpenBCI	Yes	Moderate (DIY; needs expertise)

Companies like g.tec medical engineering offer high fidelity research and medical systems, including those marketed for children [3, 14]. Similarly, NeuroSky provides accessible EEG biosensors often integrated into entertainment and educational applications, demonstrating the feasibility of using BCI for game control and mental wellness in children, such as in the game *MindLight* [3, 15]. The accessibility and proven integration with gaming environments make these high suitability platforms for reference, showing that child friendly BCIs are not just theoretical but practically achievable.

While commercial options exist, systems from companies like ANT Neuro or OpenBCI often require customization or high levels of expertise for implementation, as shown in Table 2.2, underscoring the need for a tailored engineering solution [3,16,17]. The project utilizes a custom hardware architecture based on the ADS1299 Analog Front End (AFE) IC [3]. This choice, rather than relying on standard commercial headsets, is critical for clinical robustness. The high Common Mode Rejection Ratio (CMRR) and 24-bit resolution are necessary to mitigate the external electrical interference commonly found in hospital environments [3]. This custom approach ensures the system is optimized for the unique and challenging environment of a severely disabled, ventilator dependent pediatric patient, where every millivolt of signal clarity matters.

2.3 Signal Processing

The reliability and accuracy of any BCI system fundamentally rely on robust signal processing, which converts raw electroencephalography (EEG) data into meaningful control signals. Effective processing is critical for this pediatric application due to high levels of physiological noise common in EEG acquired from children, especially those dependent on life support equipment [7]. Think about it: eye movements, muscle activity, cardiac rhythms all of these create electrical signals that can swamp the subtle brain waves we're trying to detect. The processing pipeline generally involves three stages: filtering, artifact mitigation, and feature extraction/classification.

2.3.1 Artifact Mitigation

Physiological artifacts originating from outside the brain often contaminate raw EEG signals, leading to false positives or reduced classification accuracy. Ocular artifacts from blinking, muscle artifacts from jaw clenching, cardiac activity from the heartbeat these are constant sources of interference. Therefore, effective artifact mitigation is mandatory prior to decoding the brain state.

Existing literature highlights the efficacy of hybrid signal separation methods for removing these contaminants. Specifically, Independent Component Analysis (ICA) is a primary technique that decomposes the multivariate raw EEG signal into a set of statistically independent components, under the assumption that artifacts and brain signals are statistically independent sources [7]. The beauty of this approach lies in its statistical foundation. Artifactual components (e.g., EOG from eye blinks) can then be identified and removed, allowing the remaining clean components to be reconstructed into an artifact free EEG signal.

To enhance this process, time frequency methods like the Wavelet Transform (WT) are often paired with ICA [7]. WT is crucial for denoising, particularly due to its ability to decompose the signal into frequency bands over time. Wavelet denoising works by using scaleable wavelets to threshold noise related coefficients within the decomposed signal, followed by reconstruction to yield a cleaner signal [18]. This wavelet ICA hybrid methodology is a robust approach to achieving high signal integrity, which is essential given the potentially high noise environment of the patient's bedside. Adaptive filtering techniques are also critical in mitigating ambient electrical noise, such as the 50 Hz power line interference, thus improving the signal to noise ratio before further processing stages [19]. Without these preprocessing steps, the downstream classification algorithms would be working with garbage data.

2.3.2 Feature Extraction for SSVEP

The choice of feature extraction heavily dictates the success of BCI paradigms. SSVEP based BCIs require methods that can robustly identify the subtle neural response at the exact frequency of the visual stimulus (Flicker Frequency, F_f). The feature extraction can was used in 2 dominant approaches: Traditional methods and Deep Learning methods.

Traditional SSVEP Feature Extraction

The established gold standard in SSVEP feature extraction is Canonical Correlation Analysis (CCA). CCA maximizes the correlation between the multi channel EEG signals and a set of synthetic reference signals corresponding to the target flicker frequencies. CCA is favored due to its simplicity, speed, and high performance in non intrusive settings [3]. Another fundamental approach is frequency domain analysis, often using the Fast Fourier Transform (FFT), which measures the power spectrum density (PSD) at the target flicker frequencies and their harmonics to identify the dominant, task related brain activity. FFT is computationally efficient and provides immediate insight into which frequency dominates the neural response.

Deep Learning Based SSVEP Feature Extraction and Classification

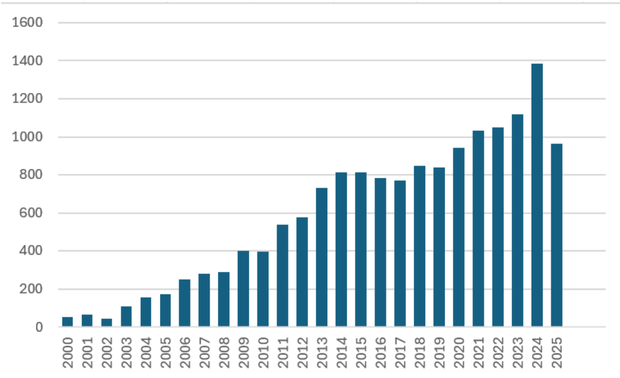
More recent research leverages deep learning to automatically learn hierarchical features, bypassing manual feature engineering. Convolutional Neural Networks (CNNs) are widely utilized as classifiers for SSVEP signals, automatically extracting frequency and spatial features for superior performance compared to traditional methods in some contexts [10]. The network learns what matters through training data rather than requiring explicit programming of feature extraction rules.

Furthermore, advanced architectures like the Transformer based Deep Neural Network Model have been shown to be effective for SSVEP classification by modeling long range dependencies within the signal data [11]. This approach can effectively model the time varying characteristics of EEG, a potentially valuable capability when dealing with the variable neural patterns observed in pediatric patients. Children's brain signals can be less consistent than adults', making these adaptive models particularly attractive.

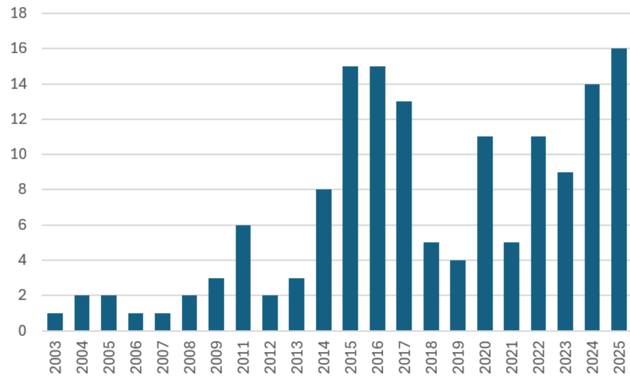
The selection between deep learning models (like CNN or Transformer) and traditional methods like CCA is often a trade off between maximizing performance (Deep Learning) and maintaining interpretability and minimal calibration time (CCA). A hybrid approach, such as those combining motor imagery with SSVEP paradigms, also necessitates robust feature pipelines capable of handling multiple input signals [12]. The decision ultimately depends on the specific application requirements and available computational resources.

2.4 Research Gap

The review of existing BCI research and commercial devices highlights a significant gap in BCI technologies tailored specifically for pediatric patients. Pediatric BCI development remains scarce due to several challenges, including the difficulty of data collection from children, variability in developmental stages, and the complexity of training pediatric patients to use BCI systems effectively. This gap indicates a critical need for child focused BCI paradigms and adaptive algorithms that account for these unique challenges. Figure 2.1 starkly illustrates this disparity: while overall BCI research has grown exponentially over the past two decades, pediatric focused BCI research remains a small fraction of the total output, demonstrating how underserved this population truly is.



(a) Evolution of BCI Research (PubMed keyword: 'Brain Computer Interface')



(b) Evolution of Pediatric BCI Research (PubMed keyword: 'Brain Computer Interface Pediatric')

Figure 2.1: Comparison of overall BCI research growth versus pediatric focused BCI research.

Chapter 3

Methodology

3.1 Project Breakdown and Timeline

3.1.1 Project Breakdown

Table 3.1: System modules for EEG based BCI development.

01. Analog Front End	Custom EEG Headset Design Adaptation and integration of existing analog hardware
02. Signal Artifact Mitigation	Implementation of baseline filters
03. Signal Processing Unit	Design and validation of classifiers for SSVEP & P300 Detection Motor Imagery (MI) Analysis
04. User Control Interface	Basic HMI Prototype for SSVEP and P300 Advanced Control Systems with all 3 PARADIGMs

3.1.2 Timeline

The proposed timeline for the project is shown in the Figure 3.1

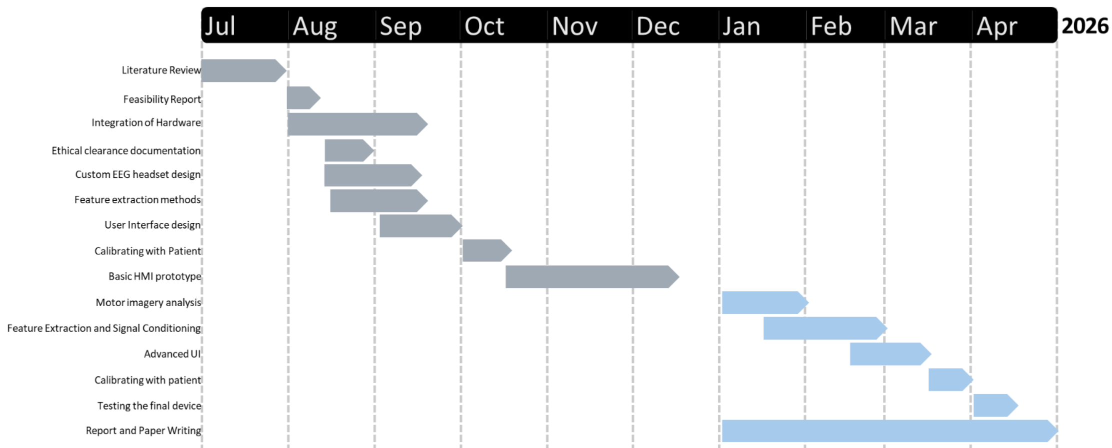


Figure 3.1: Proposed Timeline for the project

3.2 Deliverables

- Custom EEG headset for pediatric use.
- Complete BCI application with signal processing pipeline.
- Optimized decoding algorithms (MI, SSVEP, P300).
- Publication submission based on project results.

3.3 System Block Diagram

The proposed complete BCI system architecture integrates stimulus presentation, signal acquisition, processing, and control outputs into a cohesive framework. Figure 3.2 illustrates the end to end workflow from stimulus generation through EEG capture, front end hardware processing, digital filtering and machine learning classification, to final controller outputs for cursor, game, or robot control.

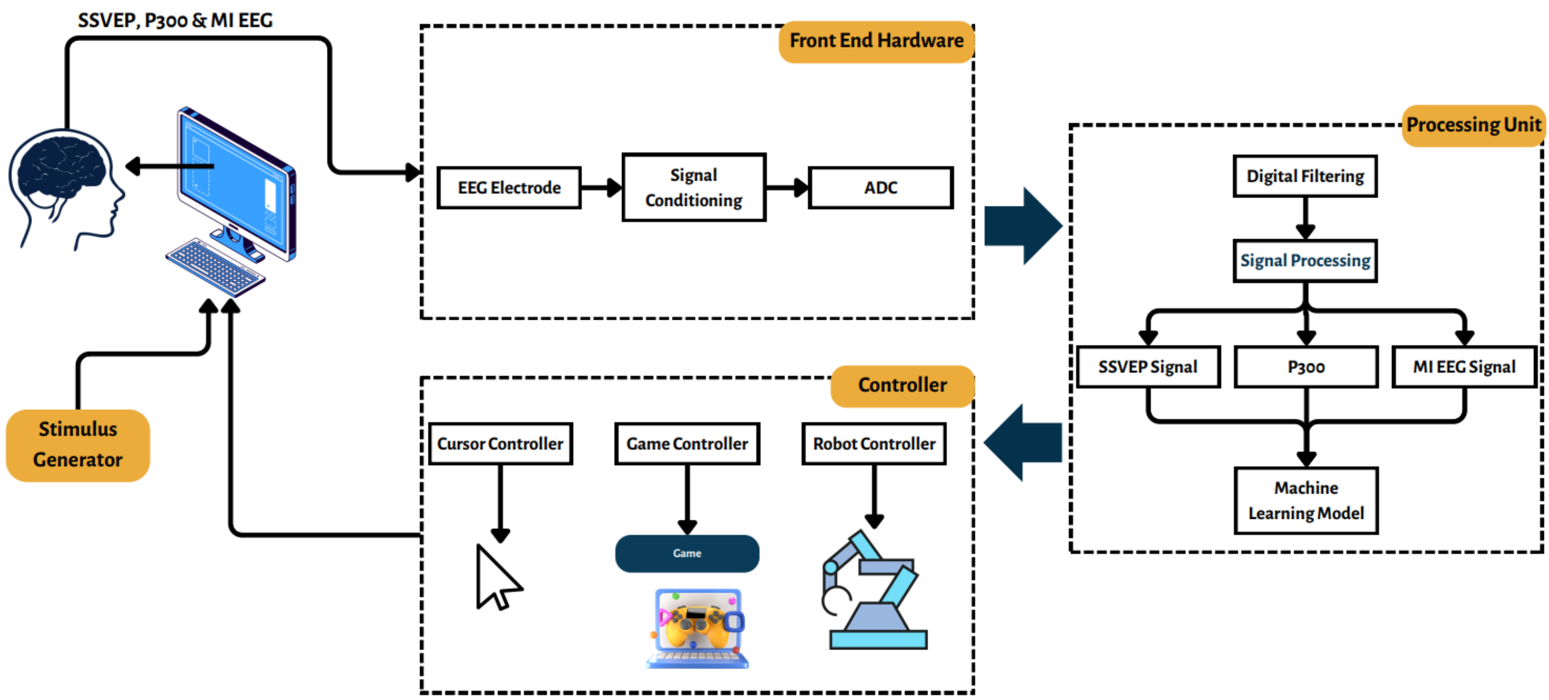


Figure 3.2: Block diagram of the proposed complete BCI system architecture

3.4 Electrode Placement 10/20 System

The 10/20 system provides a standardized method for electrode placement across the scalp, ensuring reproducibility and consistency in EEG recordings. Figure 3.3 illustrates this systematic layout, showing the internationally recognized electrode positions named according to underlying brain regions and hemisphere locations.

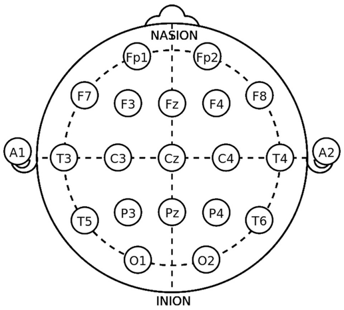


Figure 3.3: 10/20 EEG Placement Method - Source: Wikipedia

3.5 EEG Techniques Employed

The proposed BCI system follows the pipeline: EEG electrodes → analog conditioning → ADC → digital filtering → signal processing & ML → controller output (cursor/game/robot). The system will primarily leverage SSVEP, P300, and MI.

3.5.1 Steady State Visually Evoked Potentials (SSVEP)

SSVEP works by exciting a rhythmic response over the visual cortex when a user focuses on a flickering target [3, 20]. Visual targets are set to flicker at distinct frequencies, typically ranging from 6 to 20 Hz, and the brain naturally synchronizes its response to match these frequencies. The gaze locked response can then be detected via EEG, providing a direct window into what the user is attending to.

This paradigm offers several compelling advantages. It delivers a high information transfer rate, requires minimal training for users to master, and proves remarkably robust across different conditions and individuals. However, there are several drawbacks in this paradigm. Users often experience visual fatigue during extended sessions, and the approach fundamentally requires intact vision to function. For pediatric locked in syndrome patients, SSVEP shows high suitability since it relies primarily on visual attention rather than complex motor planning or communication abilities. As shown in Figure 3.4(a), the most prominent EEG signals appear at electrode positions C3 and C4 according to the 10/20 International System, with the visual cortex lighting up when users focus on flickering stimuli (Figure 3.4(b)).

(a) SSVEP Signal Most Prominent Region

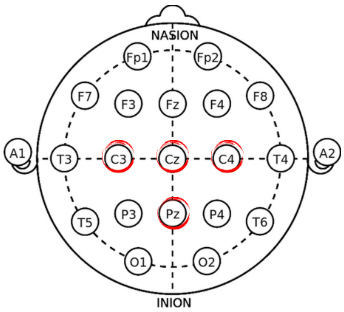
(b) How SSVEP Works [21]

Figure 3.4: SSVEP Signal characteristics and mechanism

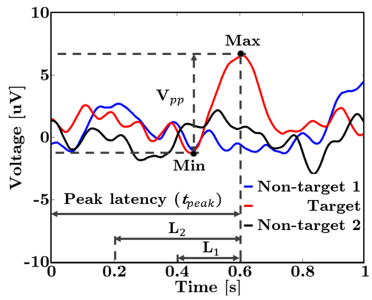
3.5.2 P300

The P300 represents an Event Related Potential (ERP) that emerges approximately 300 ms after a rare or attended stimulus appears within an oddball paradigm [4, 16]. When stimuli are intermixed imagine symbols flashing on a screen in random order infrequent target stimuli naturally capture the user's attention and evoke a distinctive P300 wave that can be used for selection tasks.

What makes P300 better is that it requires no training and proves highly effective for communication applications. The main limitation comes from its speed. Because reliable detection requires averaging multiple trials, the system operates more slowly than SSVEP. Additionally, performance depends heavily on the user's ability to maintain attention. For pediatric locked in syndrome patients, P300 shows high suitability, especially for selection tasks, though careful consideration must be given to engagement design to maintain a child's attention over time. Figure 3.5(a) illustrates how the most prominent signals appear at midline electrode locations: Pz, Cz, and Fz in the 10/20 International System. The characteristic waveform, depicted in Figure 3.5(b), shows the distinctive positive peak occurring roughly 300 ms after the target stimulus.



(a) P300 Signal Most Prominent Region



(b) Example of P300 Waveform [22]

Figure 3.5: P300 characteristics: scalp distribution and waveform

3.5.3 Motor Imagery (MI)

Motor imagery modulates sensorimotor rhythms through event related desynchronization and synchronization in the motor cortex when users imagine movements [23, 24]. This paradigm taps into two main frequency bands that reveal what the brain is doing during imagined motion.

Mu Waves (8 - 12 Hz, 10 - 100 μV)

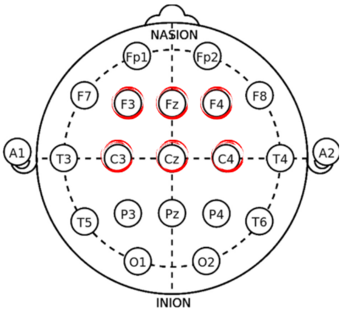
Mu rhythms dominate the sensorimotor cortex, showing up most clearly at electrodes C3, C4, and Cz. When a user imagines or executes movements picture someone mentally rehearsing a hand grasp these rhythms decrease in amplitude, a phenomenon called event related desynchronization. This makes mu waves a primary feature for MI based BCI control, essentially turning imagined movements into detectable neural signatures.

Beta Waves (13 - 30 Hz, 5 - 50 μV)

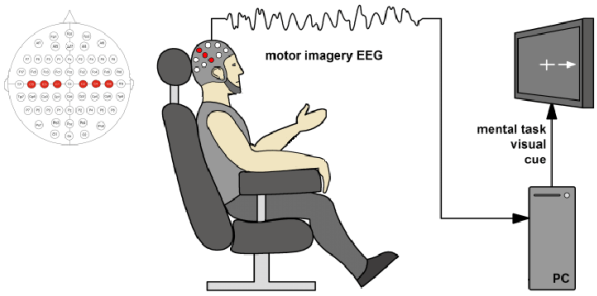
Beta rhythms appear across both central locations (C3, C4, Cz) and frontal regions (F3, F4, Fz). They're intimately associated with focused thinking and movement planning.

Like mu rhythms, beta waves also show desynchronization and synchronization during motor imagery, providing complementary information that improves classification accuracy.

Motor imagery offers an intuitive approach for motor control applications and doesn't require any external stimuli, which is a significant advantage. But there's a catch. It requires extensive training, and performance varies dramatically across users. For children especially, mastering motor imagery can prove difficult, limiting its applicability in pediatric populations. Figure 3.6 displays the scalp distribution of motor imagery signals and the underlying neural mechanisms that make this paradigm work.



(a) Motor Imagery Signal Most Prominent Region



(b) How Motor Imagery Works [25]

Figure 3.6: Motor Imagery characteristics: scalp distribution and mechanism

3.6 Hardware: Custom EEG Headset

The hardware design focuses on creating a lightweight, adjustable cap specifically sized for pediatric users. We're opting for dry or semi dry electrodes to maximize comfort and enable rapid setup critical factors when working with children. The overarching design goal is threefold: maximize comfort during extended wear, minimize the preparation time before each session, and ensure stable signal acquisition throughout use.

3.7 Multi Electrode Design

3.7.1 Dry Comb Electrodes

Dry comb electrodes feature a distinctive comb like structure with multiple prongs extending from a base, as seen in Figure 3.7.The prongs are specifically engineered to penetrate through hair and establish good scalp contact in hairy regions where traditional flat electrodes would struggle.

3.7.2 Dry Flat/Foam Electrodes

In contrast, dry flat electrodes consist of a circular base topped with foam contacts. This configuration provides a broad surface area that distributes pressure evenly, making them ideal for hairless regions like the forehead or behind the ears. The foam material conforms gently to the skin's contours. Figure 3.8 shows both circular and rectangular variants of this electrode type.

Figure 3.7: Dry Comb Electrode - Source: Internet

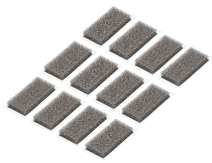


Figure 3.8: Dry Flat Electrode - Source: Internet

3.7.3 Active Dry Electrodes with Snapping Method (From Previous Groups)

Building on work from previous project groups, we're incorporating active dry electrodes with an innovative snapping mechanism. The snapping system built into the electrode pins eliminates the discomfort of traditional pinned electrodes while maintaining secure contact. More importantly, these active electrodes integrate amplification circuitry directly at the sensing site, dramatically reducing noise in the acquired signals. The circuit design from the BraiNeoCare 2023 project (Figure 3.9) demonstrates the active electronics integrated into each electrode, while Figure 3.10 showcases the mechanical snapping designs developed by the 2024 team.

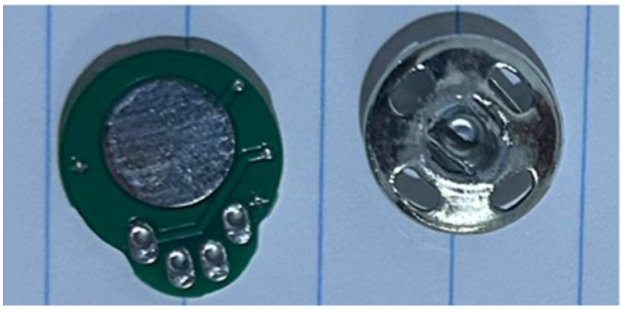


Figure 3.9: Active Electrode Circuit from BraiNeoCare 2023 Final Report

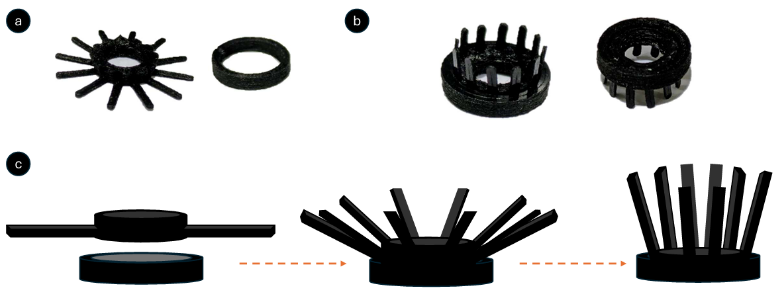


Figure 3.10: Active Dry Electrode Designs from BraiNeoCare 2024 Final Report

3.8 EEG Amplifier and Signal Conditioning

Table 3.2: Comparison of EEG amplifier and signal conditioning ICs.

IC Model	Type	Ch.	Input Noise	CMRR	Power (per ch.)	ADC	Max Rate
ADS1299	Analog Front End (SoC)	8	1 μV_{pp}	120 dB	5 mW	Yes, 24-bit	16 kSPS
INA128	Instrumentation Amplifier	1	0.7 μV_{pp}	120 dB	5 mW	No	
AD620	Instrumentation Amplifier	1	0.9 μV_{pp}	100 dB	6.5 mW	No	
RHA2216	Analog Front End Amplifier	16	1.2 μV_{pp}	110 dB	6 mW	Yes, 24-bit	8 kSPS

After evaluating multiple options shown in Table 3.2, we've selected the ADS1299 as our primary signal conditioning device. This 8 channel integrated circuit incorporates a 24-bit delta sigma ADC, delivering the precision we need for capturing subtle EEG signals. What sets the ADS1299 apart is its exceptionally low noise floor and high common mode rejection ratio [6], both critical for pulling clean neural signals out of the electromagnetic chaos surrounding any recording environment. The device serves a dual purpose: amplifying the microvolt level EEG signals to a range suitable for processing while simultaneously digitizing them for reliable computational analysis.

3.9 Signal Preprocessing

3.9.1 Filters

Filters are applied to remove unwanted noise and retain the frequency components of interest in the signal. Without proper filtering, the subtle brain signals we're trying to detect would be buried under layers of environmental and physiological noise.

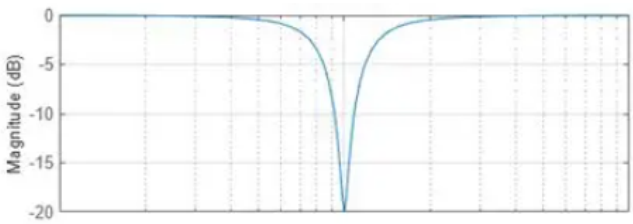
50 Hz Notch Filter

The 50 Hz notch filter is designed to eliminate power line interference, which is a common artifact in electrical signal recordings caused by alternating current in the environment.

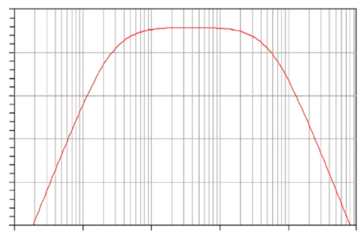
This filter specifically attenuates the signal at 50 Hz while preserving the surrounding frequencies, ensuring that nearby brain wave frequencies remain intact. Figure 3.11a shows the sharp frequency response of this notch filter, demonstrating its precision in targeting only the problematic frequency while leaving adjacent frequency bands untouched.

0.5 70 Hz Band pass Filter

The band pass filter allows frequencies between 0.5 Hz and 70 Hz to pass through, effectively removing very low frequency drifts and high frequency noise. Low frequency drifts typically arise from electrode movement or slow changes in skin conductance, while high frequency noise comes from muscle artifacts or electromagnetic interference. This frequency range is particularly suitable for applications like EEG signal processing, where brain waves typically fall within these bounds. As illustrated in Figure 3.11b, the filter's frequency response shows clear attenuation outside the desired passband, creating a clean window for capturing neural activity.



(a) Frequency response of the 50 Hz notch filter.



(b) Frequency response of the 0.5–70 Hz band-pass filter.

Figure 3.11: Frequency responses of the designed filters.

3.9.2 Physiological Artifact Mitigation

Artifact mitigation techniques are employed to identify and remove non signal components from other biological sources that could distort the analysis. Ocular artifacts from eye movements and blinks can create massive voltage swings that dwarf brain signals. Muscular artifacts from facial tension or jaw clenching introduce high frequency contamination. Figure 3.12 displays examples of these common physiological artifacts in EEG signals, showing how dramatically they can corrupt the underlying neural data we're attempting to decode. Recognizing these patterns is the first step toward removing them effectively.

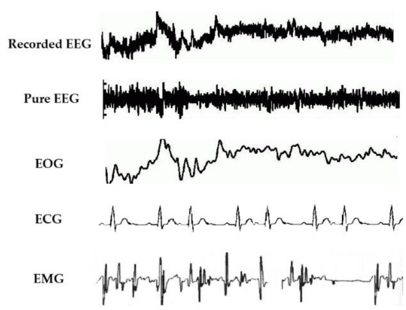


Figure 3.12: Examples of common physiological artifacts in EEG signals. [1]

Wavelet Transform (WT)

The wavelet transform decomposes the signal into different frequency components using scalable wavelets, enabling time frequency analysis. It is effective for denoising and artifact removal by thresholding coefficients associated with noise, allowing reconstruction of a cleaner signal [7].

Independent Component Analysis (ICA)

Independent component analysis separates the mixed signal into statistically independent sources, assuming non Gaussian distributions. In signal preprocessing, ICA is used to isolate and remove artifacts like eye blinks or heartbeats from the primary signal of interest [7].

3.10 Paradigm Based Controller

3.10.1 Controller Pipeline

The controller follows a pipeline from raw EEG to command output (Fig. 3.13). Raw signals undergo preprocessing (filtering and artifact removal), then parallel processing units extract features and classify SSVEP, Motor Imagery, and P300 paradigms. Command mapping translates classified brain states into directional commands: up, down, left, right, front, and back.

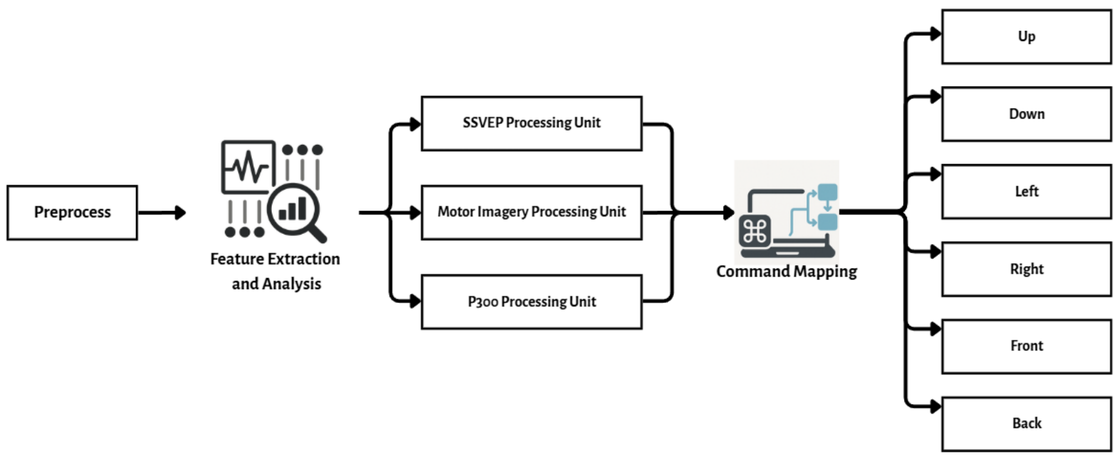


Figure 3.13: Controller pipeline architecture from preprocessing to command output

3.10.2 Feature Extraction and Classification

Following a review of the literature for feature extraction methods, we identified both traditional and deep learning approaches. The decision tree shown in Figure 3.14 maps out our strategy.

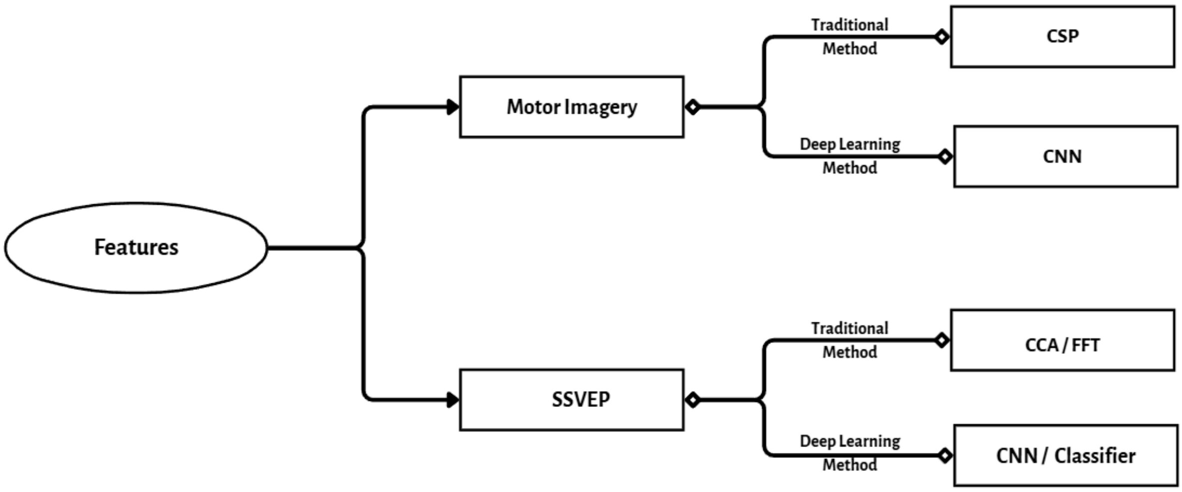


Figure 3.14: Feature extraction and classification methods for different BCI paradigms

For Motor Imagery, we're considering Common Spatial Pattern (CSP) as the traditional method or CNN based pipelines for deep learning [9, 12]. For SSVEP, the options include Canonical Correlation Analysis (CCA) and FFT baselines as traditional approaches, while CNN and Transformer models represent the deep learning path [10,11,20]. We plan to select a suitable method when commencing the project, based on performance and applicability in the pediatric context.

3.11 Datasets

Dataset	**sEEG**	**Paradigm**	**Pediatric**	**Channel wise Data**
Benchmark Dataset	✓	SSVEP	×	✓
MAMEM	✓	SSVEP	×	✓
ssvep_sandiego	✓	SSVEP	×	✓
PhysioNet EEG Motor Movement	✓	Motor Imagery	×	✓
GigaScience Dataset	✓	Motor Imagery	×	✓
BNCI2014 002	✓	Motor Imagery	×	×

Table 3.3: Summary of benchmark EEG datasets with their paradigms, pediatric relevance, and availability of channel wise data.

- **Personalization:** Fine tune models on pediatric subject specific sessions.

3.12 User Interface

3.12.1 How SSVEP BCI Works

The SSVEP BCI mechanism begins when a user gazes at a target that flickers at a specific frequency, eliciting a steady state visually evoked potential in the visual cortex.

The interface displays multiple flickering stimuli, each oscillating at distinct frequencies or phases. Each flicker corresponds to a specific command, allowing the user to select actions simply by shifting their gaze. This elegant approach enables video stream integration with embedded flickers for real time control, creating an intuitive interaction paradigm.

This approach can be used for creating selections within the patient's favorite game, where different game elements blink at different frequencies [2]. Figure 3.15 demonstrates how flickering stimuli can be integrated into an interface design, showing the feasibility of embedding such controls directly into patient game interactions. The visual elements become both entertainment and control mechanism simultaneously.

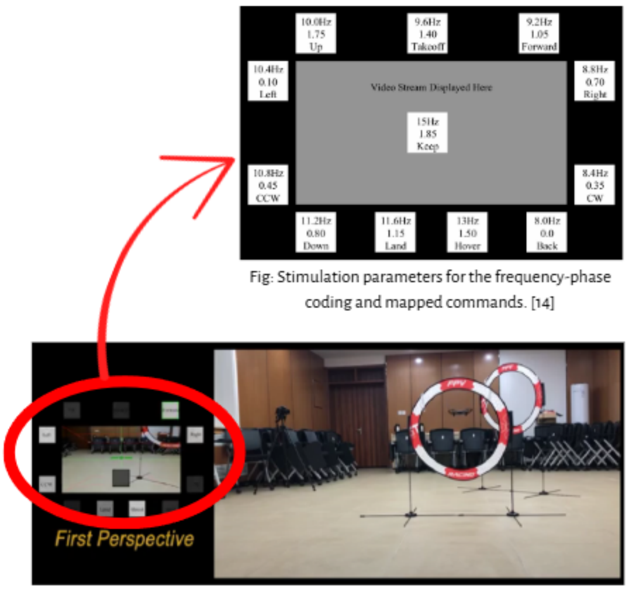


Figure 3.15: SSVEP based interface design showing flickering stimuli for command selection, demonstrating feasibility for patient game interactions [2]

3.12.2 Proposed Implementation

Based on this principle, we propose to implement SSVEP driven menus for directional or game commands, allowing the child to navigate through options naturally using their gaze. Personalized themes will enhance engagement by incorporating the child's favorite characters and colors into the interface design. Optional auditory cues will assist user interaction, providing feedback when selections are made or when the system detects sustained attention on a particular target. Reward loops will sustain motivation and attention throughout extended sessions, critical for maintaining a child's engagement during therapy or play.

Figure 3.16 shows the game Lucas and Friends, which represents the type of beloved content we aim to integrate with BCI control. By embedding flicker frequencies into familiar game elements, we can transform existing entertainment into a therapeutic control interface that children already want to engage with.

Figure 3.16: Game Lucas and Friends UI the game that the child loves - Source: Lucas & Friends Game

Chapter 4

Discussion

4.1 Key Findings

Pediatric centric BCI solutions are currently limited. A non invasive, comfort first design combined with engaging interaction strategies is critical for usability and clinical adoption.

4.2 Feasibility and Risk

Technical Feasibility: Implementation is possible with commercial off the shelf (COTS) components. **Technical Risks:** EEG signal noise or artifact interference (e.g., muscle movement, electrode drift). *Mitigation:* Adaptive signal filtering, robust artifact rejection algorithms, and well designed electrode placement. Calibration delays due to individual brain pattern variability. *Mitigation:* Use of short calibration mini games, machine learning models that adapt over sessions, and semi supervised calibration techniques.

Medical Risks: Potential discomfort from EEG headsets in pediatric use. *Mitigation:* Lightweight, adjustable, comfort first cap design with soft padding. Limited clinical validation for young Locked in Syndrome patients. *Mitigation:* Collaborate with pediatric clinicians for trials and progressively expand patient validation cohorts.

Financial Risks: Funding is partially sourced from the patient's family (negotiable amount). Overseas shipment required for certain electronic components (e.g., microcontrollers, amplifiers).

Social Feasibility: Strong quality of life benefits by enabling communication and interactive play. Research support from collaborators (e.g., Lady Ridgeway Hospital) for medical guidance, and additional backing for paper submission and dissemination.

4.3 Impact

Local: Immediate, tangible benefits for the patient and clinical care team, with improved interaction and communication channels.

Global: Expands the evidence base for pediatric BCI systems and contributes open designs to the BCI community, lowering barriers to adoption in similar use cases.

Chapter 5

Conclusion

In conclusion, this feasibility study on the development of an Assistive Care Brain Computer Interface (BCI) for a locked in pediatric patient represents a significant step forward in addressing the profound challenges faced by children with Locked In Syndrome (LIS). By leveraging non invasive EEG based technologies specifically Steady State Visually Evoked Potentials (SSVEP), P300 event related potentials, and Motor Imagery (MI) paradigms the proposed system aims to bridge the gap between the patient's intact cognitive abilities and their severely limited physical interactions. For the 6 year old boy at the center of this project, who transitioned from a playful, talkative child to one paralyzed by acute flaccid myelitis and ventilator dependent, this BCI offers a lifeline: a means to engage with video games, cartoons, toys, and other stimuli that once brought him joy, thereby restoring a sense of autonomy and reigniting his interest in life.

The project's foundation is rooted in a thorough literature review that underscores the scarcity of pediatric specific BCI solutions, while highlighting promising contributions from research groups like the University of Calgary and TU Graz, which emphasize play based motivation and game control. Commercially, non invasive products from companies such as g.tec and NeuroSky provide viable building blocks, though customization for a child friendly design is essential. Our methodology, encompassing a custom dry electrode EEG headset, advanced signal processing with the ADS1299 amplifier, artifact mitigation via wavelet transform and independent component analysis, and machine learning driven feature extraction (e.g., CNN for SSVEP and CSP for MI), addresses key limitations of conventional BCIs such as prolonged training and fatigue through built in trainers, reward driven loops, and minimal setup requirements.

From a feasibility perspective, the technical aspects are robust, supported by accessible datasets for initial training and patient specific fine tuning to overcome the lack of pediatric data. Financially, partial support from the patient's family, combined with guidance from Lady Ridgeway Hospital collaborators, mitigates resource constraints, while risks like signal noise or headset discomfort are manageable through adaptive filtering and ergonomic design. Socially and ethically, this initiative aligns with the moral imperative articulated by researchers like Dr. Kirton, viewing BCI access for children as a human right that enhances daily well being and development.

Looking ahead, successful implementation could extend beyond this individual case, paving the way for broader applications in pediatric neurology and assistive robotics. By enabling locked in children to interact independently, the project not only promises to improve quality of life but also contributes to global advancements in neurotechnology, potentially inspiring scalable solutions for similar conditions worldwide. Ultimately, this feasibility report affirms the project's viability, with managed risks and high potential impact, setting the stage for prototype development, clinical testing, and a research publication that could transform lives one brain signal at a time.

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