# Chapter 2

# An Affordable Brainwave Reader to Help People with Motor Neurone Disease (MND) Communicate via Thoughts Using Novel AI Technology

**Amin Al-Habaibeh[1]*, Sharmila Majumdar[1], and Ahmet Omurtag[2]**

[1]Product Innovation Centre, Product Design, Nottingham Trent University, Nottingham, UK
[2]Engineering Department, Nottingham Trent University, Nottingham, UK

## Abstract

Brain–computer interface (BCI) technology provides a method of communication for people whose motor neurons are impaired and unable to communicate but their cognition is preserved as in the case of motor neurone disease (MND). This paper reports the design and evaluation of a low-cost, non-invasive EEG-based BCI prototype that could provide families and health carers with a solution to effectively communicate with a person with physical and speech disability, such as completely locked-in-syndrome (CLIS). As a low-cost technology, it could also support patients in developing countries where other technologies might be unaffordable. The first developed system, named Responsive Assisted Dialogue version 1 (RAD1), recognises two mental imagery states and maps them to simple communication outputs, this to support 'yes/no' or 'option1/option2' communication to provide patients with a communication tool. The system employs three EEG electrodes across the head and data are processed using artificial intelligence (AI) and a modified version of the novel Automated Sensory and Signal Processing (ASPS) approach. The extracted sensory features are fed into a Feed Forward Neural Network (FFNN) classifier. The results, using healthy volunteers and a volunteer with MND, indicate a very positive result to identify key communication messages via imaginations.

**Keywords:** *Artificial Intelligence, Brain, EEG, BCI, ANN, ALS, MND, CLIS*

## Introduction

Brain–computer interface (BCI) enables information transfer directly from neural activity by sensing and decoding brain signals. This paradigm is particularly relevant for motor neurone disease (MND) patients, where progressive degeneration of motor neurones disrupts voluntary movement, but capacities such as imagination and memory often remain intact. In amyotrophic lateral sclerosis (ALS), a major subtype of MND, BCIs have been shown to preserve communication even in severe disability or completely locked-in syndrome (CLIS)[1]. Al-Habaibeh (2025) has highlighted in his recent article the future of chip implants for Brain–Computer Interface where invasive technologies are being tested with

---

[1] Ioulietta Lazarou et al., "EEG-Based Brain–Computer Interfaces for Communication and Rehabilitation of People with Motor Impairment: A Novel Approach of the 21st Century," Frontiers in Human Neuroscience 12, no. 14 (January 31, 2018), https://doi.org/10.3389/fnhum.2018.00014

**DOI: 10.18502/rq457c78_2**

implants directly placed on the brain's surface[2]. Such invasive technologies require sophisticated medical and surgical procedures hence making it an expensive option.

Among numerous non-invasive brain imaging systems, electroencephalography (EEG) is widely used due to high temporal resolution, non-invasive operation, portability, and affordability. EEG contributes substantially to diagnosis and to biomedical engineering research and underpins many BCI approaches[3]. Patients with ALS typically have limited communication options: eye-activity systems (e.g., gaze trackers) can demand continuous effort, induce fatigue, and become impractical in supine positions; in contrast, cognitive-activity BCIs (e.g., motor imagery) offer greater comfort and flexibility[4].

This study presents an affordable EEG-BCI that detects two distinct mental imagery states and translates them into binary outputs for basic communication (e.g., "*Yes/No*"). The objectives were to: (i) design a low-cost EEG prototype; (ii) implement it using cost-effective, reliable components; (iii) acquire signals under a controlled protocol; (iv) process and analyse signals within an AI and ASPS signal analysis framework; (v) deliver a simple graphical user interface (GUI) software for acquisition, processing, and communication; and (vi) evaluate system performance. The emphasis is on simplicity, reproducibility, and feasibility in resource-constrained settings. To overcome the challenges of sensory feature extraction and the integration with AI, Al-Habaibeh and Gindy (2000) proposed the ASPS approach, which automates feature discovery and selection from sensory signals[5]. Majumdar et al. (2023) investigated the ASPS approach in brain signal processing and has demonstrated high accuracy to recognise different number of imaginations[6]. Figure **1** presents the block diagram of the modified ASPS approach for brain signal processing.

The ASPS approach for BCI technology is based on extracting the EEG signals as in Figure **1**A and processing it using a wide range of signal processing methods (Figure **1**B) to produce sensory characteristic features (SCFs) that are organised for each sensor and signal processing method in a 3D matrix (Figure **1**C). Following that, the sensitivity or dependency of each SCF on the imagination is organised in an association matrix, (Figure **1**D). The behaviour of SCFs is combined to create unique patterns (Figure **1**E). The AI system is trained on the relationship between a group of SCFs and the

---

[2] A. Al-Habaibeh and N. Gindy, "A New Approach for Systematic Design of Condition Monitoring Systems for Milling Processes," *Journal of Materials Processing Technology* 107, no. 1–3 (November 1, 2000): 243–51, https://doi.org/10.1016/s0924-0136(00)00718-4

[3] Katarzyna Blinowska and Piotr Durka, "Electroencephalography (EEG)," *Wiley Encyclopedia of Biomedical Engineering*, April 4, 2006, https://doi.org/10.1002/9780471740360.ebs0418

[4] Liliana García et al., "A Comparison of a Brain-Computer Interface and an Eye Tracker: Is There a More Appropriate Technology for Controlling a Virtual Keyboard in an ALS Patient?" in *Lecture Notes in Computer Science*, 2017, 464–73, https://doi.org/10.1007/978-3-319-59147-6_40

[5] Al-Habaibeh and Gindy, 2000, "A New Approach for Systematic Design of Condition Monitoring Systems for Milling Processes.", Journal of Materials Processing Technology, 107, pp. 243–251.

[6] Sharmila Majumdar et al., "A Novel Approach for Communicating with Patients Suffering from Completely Locked-in-syndrome (CLIS) via Thoughts: Brain Computer Interface System Using EEG Signals and Artificial Intelligence," *Neuroscience Informatics* 3, no. 2 (March 21, 2023): 100126, https://doi.org/10.1016/j.neuri.2023.100126

possible imaginations or thoughts (Figure **1**G). Following that, the AI system (neural networks) is utilised to classify the AI system in recognising the imagination of the patient (Figure **1**H). This present work aims to develop a non-invasive and affordable EEG-BCI system, named RAD1, that leverages low-cost hardware and ASPS-style feature automation and AI integration to deliver practical communication tool for MND patients.

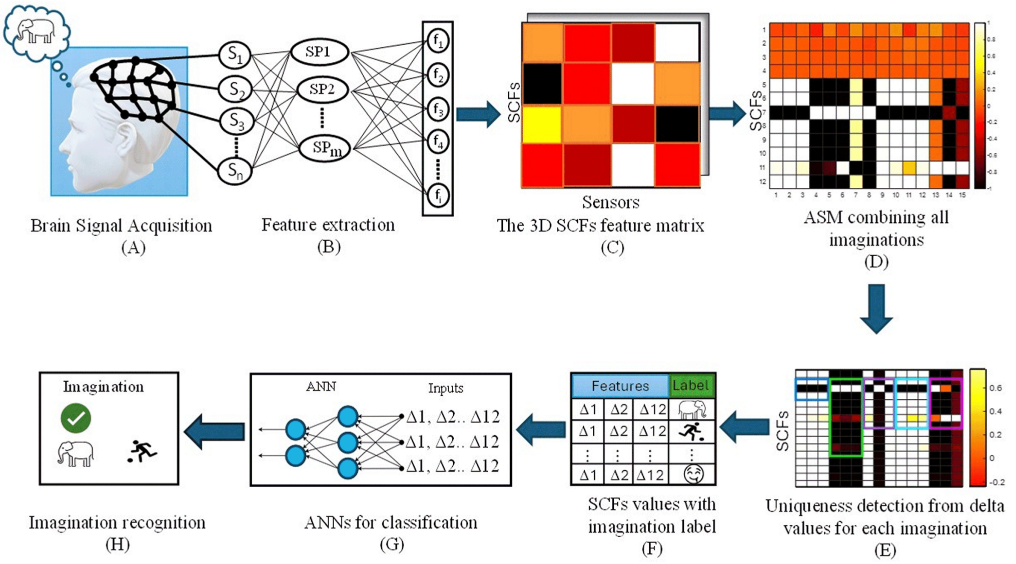


**Figure 1:** The block diagram of the ASPS approach applied to brain signal processing.

## Methodology

The RAD1 prototype was developed to combine the AI-ASPS algorithm with a low-cost hardware and computer interface to test in real-time communication via thoughts using EEG signals. A low-cost EEG board for each electrode provided the analogue EEG input and output, where the three signals are interfaced to a data acquisition board for data digitalisation and analysis using Matlab software. Figure **2** illustrates the schematic diagram of the EEG-BCI used for data acquisition.

All components were housed in a compact enclosure with a high-speed USB port for data transfer and a 3.5 mm jack for sensor connections, improving safety and repeatability. Figure **3** presents the updated system, with Figure **3**A showing the top view and Figure **3**B presenting the side view of the newly designed EEG-BCI RAD1 prototype.

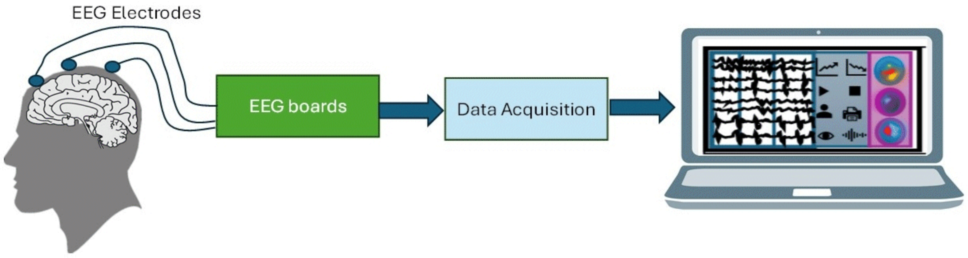


**Figure 2:** A schematic diagram of EEG-BCI for signal acquisition.

(A) The novel low-cost RAD1 prototype

(B) Top view of the RAD1 prototype

**Figure 3:** The newly developed EEG-BCI RAD1 prototype.

The electrode locations are selected to facilitate ease of placement, consistency, and patient comfort, while also aligning with optimal positions that provide EEG signals with unique signatures for the system (Figure **4**).

**Figure 4:** Signal acquisition during the testing of the newly developed EEG-BCI RAD1 prototype.

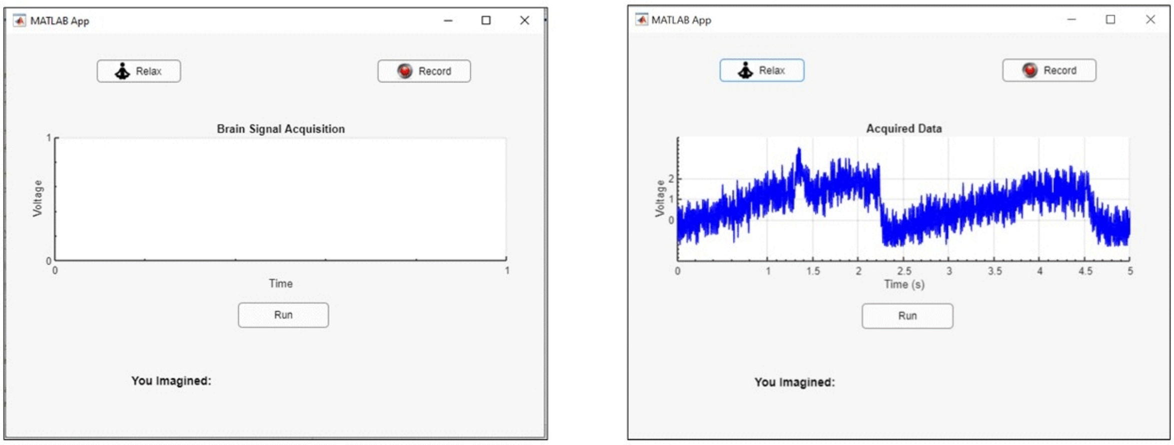
Two distinct mental tasks (imaginations) were selected from a large portfolio of imaginations from the background research: (i) imagining seeing an elephant and (ii) imagining kicking a football. Each trial began with a relaxation stage to establish baseline activity and reduce carry-over effects, followed by 5 seconds of sustained imagery on verbal instruction. Volunteers and the patient were reminded to minimise jaw tension, eye blinks and body movement to limit artefacts. Signals were acquired simultaneously from the three sensors as shown in Figure **4**.

To reduce computing demands and reduce cost, processing was focussed on frequency-domain characterisation using the ASPS approach with AI integration. For each channel, a fast Fourier transform (FFT) was computed and its magnitude spectrum partitioned into five frequency regions, guided by inspection of representative spectra. For each region, four statistical functions: mean, standard deviation, variance, and maximum, were computed, yielding 20 SCFs per channel due to dividing the frequency signal to five sections (bands). The definitions and equations are presented in Table **1**. The difference in SCFs values (Δ) helped suppressing common-mode trends and reduce noise, including the persistent 50 Hz component observed in environmental conditions from interference. The resulting features were combined and used to create a unique signature for each imagination.

**Table 1:** Definitions and equations of the four selected statistical functions to process FFT segments.

| Index | Definition | Equation |
|---|---|---|
| 1 | Mean | $E_1 = \frac{1}{n} \Sigma_{i=1}^{n} x_i$ |
| 2 | Standard deviation | $E_2 = \sqrt{\frac{\Sigma_{i=1}^{n}(x_i - E_1)^2}{N}}$ |
| 3 | Variance | $E_3 = \frac{\sum_{i=1}^{n}(x_i - E_1)^2}{N}$ |
| 4 | Max | $E_4 = max\ (x_i)$ |

A single-layer FFNN neural network received the SCFs as inputs to produce a classification output as a binary decision. To probe model capacity and stability, hidden-layer sizes from 1 to 120 neurons were evaluated. For each size, the network was trained and tested 50 times with random initialisations, and both maximum and average accuracies were recorded. A MATLAB GUI coordinated acquisition, visualisation, and output. Real-time plots displayed scrolling raw EEG and corresponding FFT spectra; a status panel reported the current classification and confidence. For demonstration, the binary decision was mapped to on-screen messages that could be connected to communication outputs (Figure **5**).



**The Graphical User Interface (GUI)**
**before recording**
**(A)**

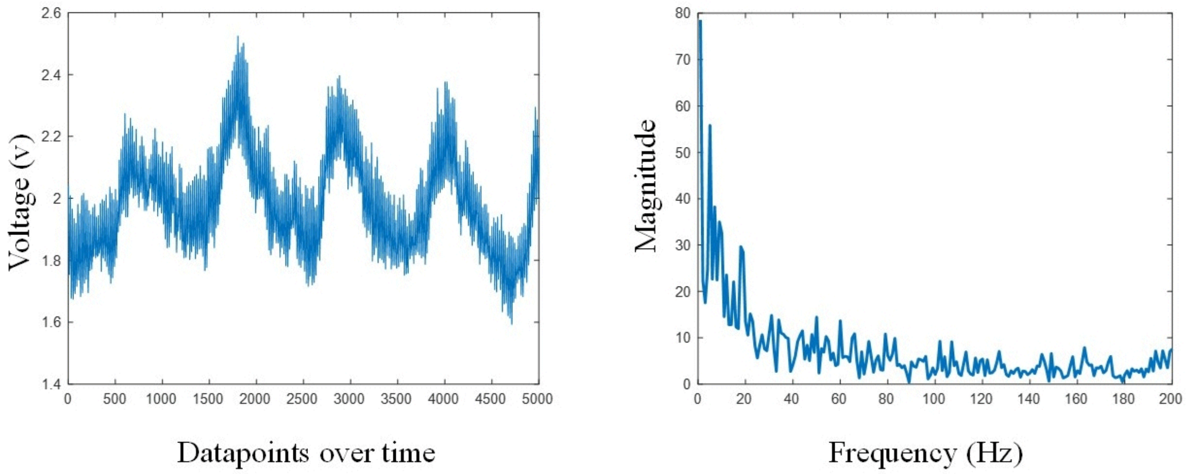
**The Graphical User Interface (GUI)**
**after recording**
**(B)**

**Figure 5:** The application view (A) before recording and (B) after recording.

The "Run" button activates the signal processing method in the background, classifies the signals, and displays the communication output on the screen. This application is designed with bespoke manner, where the internal FFNN model is trained offline for individual subjects. The system processes real-time data from the subject and generates the corresponding communication output based on the trained model. Hence providing real-time communication via thoughts.

## Results and Discussion

The FFT segments are determined by considering the FFT outcomes of the raw signals, as illustrated in Figure **6**, which displays (A) the raw signal and (B) the corresponding FFT outcome.



(A) (B)

**Figure 6:** Signal visualisation (A) of raw signal recording using EEG-BCI RAD1 prototype and (B) the associated FFT plot.

Figure **7** illustrates an example of the performance recorded over 50 runs, with a dotted line representing the mean performance across these runs. The FFT-generated SCFs yielded a maximum accuracy of 100% and an average of 79% across 50 runs.

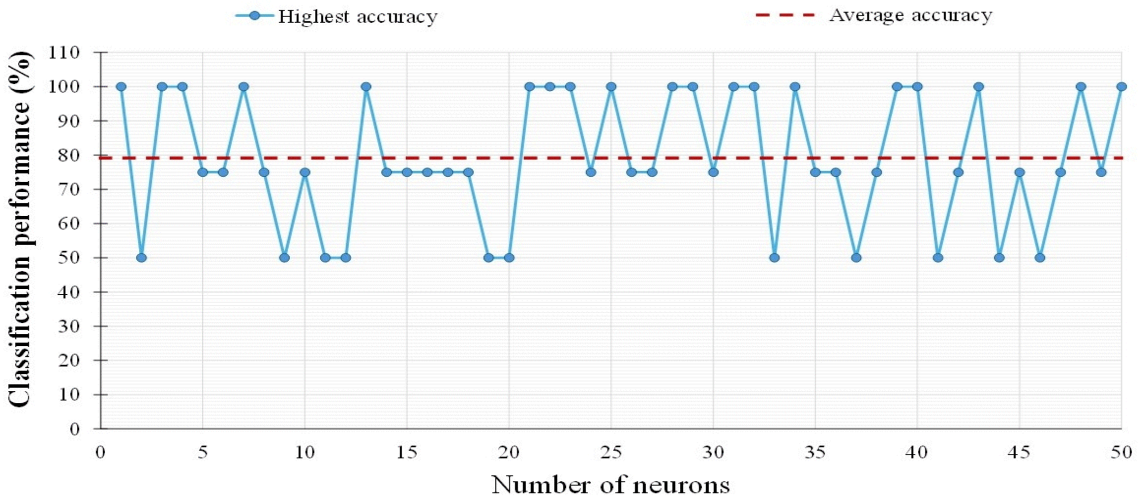


**Figure 7:** Classification performance of EEG-BCI RAD1 prototype using the ASPS approach and neural networks using five-section frequency domain generated SCFs.

The prototype captured clear signals from three sensors and displayed them in real time. Using the FFT features per segment (band), the FFNN achieved frequent 75% accuracies across hidden-layer sizes, with multiple instances of 100%. From the hardware point of view, the electrodes were easy to place, comfortable, and yielded reliable accuracies. The GUI streamlined the process from calibration to classification, while the enclosed hardware assembly simplified sensor uses and minimised error. Together, the system demonstrated practical end-to-end feasibility for thought-based communication.

The results show that the proposed non-invasive and affordable EEG-BCI can separate two mental imagery states or thoughts with reliability for communication purposes. The SCF features from five spectral bands captured discriminative patterns with low dimensionality, enabling the neural network to learn effectively from concise data. Performance averaged 79%, with 100% success with rounding the results to binary format, hence reflecting stable spectral differences between the two imaginations.

## Conclusion

This paper presented the design and evaluation of an affordable novel EEG-BCI RAD1 prototype tailored to support communication via thoughts for MND patients. Using three EEG electrodes and 1 kHz sampling rate, ASPS-guided FFT feature extraction and an FFNN neural network, the system reliably discriminated between two mental imagery states or thoughts. A high accuracy of 100% for rounded results were achieved. This proposed technology demonstrates the feasibility of low-cost, non-invasive thought-driven EEG communication using AI. Future work will include further noise reduction and additional SCFs with broader validation on diverse users.

## Acknowledgement

The authors would like to thank all volunteers for supporting this work. Special thanks to Nottingham Trent University for funding this work via the Medical Technologies and Advanced Materials Theme (Grant number 01EGI-RD066) and the PhD research sponsorship from School of Architecture, Design and the Built Environment.

## References

Al-Habaibeh, A., and N. Gindy. "A New Approach for Systematic Design of Condition Monitoring Systems for Milling Processes." *Journal of Materials Processing Technology* 107, no. 1–3 (Nov 2000): 243–51. https://doi.org/10.1016/S0924-0136(00)00718-4

Amin Al-Habaibeh, "From Brain Bluetooth to 'Full RoboCop': Where Chip Implants Will Be Heading Soon," *The Conversation*, April 11, 2025, https://theconversation.com/from-brain-bluetooth-to-full-robocop-where-chip-implants-will-be-heading-soon-254376

Blinowska, Katarzyna, and Piotr Durka. "Electroencephalography (EEG)." *Wiley Encyclopedia of Biomedical Engineering*, April 4, 2006. https://doi.org/10.1002/9780471740360.ebs0418

García, L., Ricardo Ron-Angevin, Bertrand Loubière, Loïc Renault, Gwendal Le Masson, Véronique Lespinet-Najib, and Jean-Marc André. "A Comparison of a Brain-Computer Interface and an Eye Tracker: Is There a More Appropriate Technology for Controlling a Virtual Keyboard in an ALS Patient?" In *Lecture Notes in Computer Science*, 464–73, 2017. https://doi.org/10.1007/978-3-319-59147-6_40

Lazarou, I., Spiros Nikolopoulos, Panagiotis C. Petrantonakis, Ioannis Kompatsiaris, and Magda Tsolaki. "EEG-based Brain–computer Interfaces for Communication and Rehabilitation of People with Motor Impairment: A Novel Approach of the 21st Century." *Frontiers in Human Neuroscience* 12, no. 14 (Jan 2018). https://doi.org/10.3389/fnhum.2018.00014

Majumdar, Sharmila, Amin Al-Habaibeh, Ahmet Omurtag, Bubaker Shakmak, and Maryam Asrar. "A Novel Approach for Communicating with Patients Suffering from Completely Locked-in-syndrome (CLIS) via Thoughts: Brain Computer Interface System Using EEG Signals and

Artificial Intelligence.” *Neuroscience Informatics* 3, no. 2 (Mar 2023): 100126. https://doi.org/10.1016/j.neuri.2023.100126