Plug and Play Auto-Adaptive Brain Computer Interface

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***Abstract*— This paper presents a low-cost Brain Computer Interface (BCI) specifically designed for Amyotrophic Lateral Sclerosis (ALS) patients. The BCI effectively decodes motor imagery (MI) of the left and right hand while adapting to address non-stationarities over time. The system incorporates a portable EEG acquisition device equipped with an auto-adaptive filter bank Common Spatial Pattern (CSP) algorithm, enabling accurate detection of hand MI. The evaluation results demonstrate that the BCI achieves average accuracies of 74±7% and 75±6% over a 1–2 month period of usage involving 3 ALS patients. Remarkably, the model can require as little as 6 movements of each hand for training, keeping training times low. The windowed method of data retention contributes to the BCI's success in maintaining performance and usability. The open-source acquisition device is low cost whilst providing appropriate form factor, 24+h battery life, and 18 channels with the ability to connect via SPI to any suitable device.**

Keywords—Auto-adaptive, ALS, BCI, EEG, hand, left, motor imagery, right

I. Introduction

Over 200,000 people worldwide are affected by ALS, increasing by 69% by 2040 [1]. ALS is a progressive neuromuscular disease which removes the ability for cortical neurons to communicate with muscles through gradual degradation of motor neurons. Leaving patients in highly paralysed states, with the majority of deaths linked to respiratory failure within 2-5 years of onset [2]. During movement, motor cortex neurons release action potential, where electroencephalography (EEG) can measure specific neuron output that is highly associated to specific motor task. However, with surface-EEG, there is a lack of spatial resolution. Research has shown that ALS patients can learn to modulate sensorimotor rhythms (SMR) that describe imagined movement [3, 4]. With BCI, neural signals can be acquired, conditioned, features extracted and decoded through machine learning into desired action. As shown in Fig. 1, using assistive technologies, ALS patients could gain functionality whilst preserving cognitive abilities. Training before the total locked in stage is recommended [5].

The limitation of BCI in clinical settings for ALS patients can be attributed to non-stationarities in the EEG. As the disease progresses, cortical neurons decay due to lack of use, which gradually diminishes the SMR control signal. Another non-stationarity is electrode impedance changes from sweat, hair growth and incremental changes in channel locations. Additionally, artifacts like ocular, muscular, electrical, device movement, and mood has been increasingly linked to changes in users EEG [6]. Finally, BCI Illiteracy, where not all users can achieve a benchmark of 70% classification, alluding to inter-subject differences which need to be accounted for. These variations in signal cause incremental differences in training and testing data resulting in a large reduction of

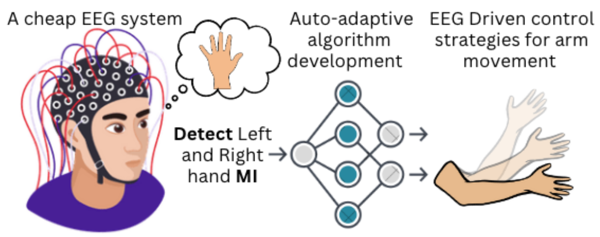

Fig. 1. Overall aim for the proposed system

prediction accuracy. Further, financial, and operational costs need to be reduced by optimising electrodes, wires, expert intervention, training, and portability [7-10]. Specifically, reducing the dependence on training would provide higher utility in clinical settings whilst simultaneously enforcing the MI skill from early stages, benefiting clinicians, researchers, and patients alike.

The state of the art has shown that regularising parameter estimation in online BCI systems may improve reliability and enable longer usage without interruption. Where training and testing data diverge, adaptive methods which push for feature space adaptation is necessary [11]. Adaption to user has been studied in many dimensions but most notable are feature space and number of channels. Bennet *et al* [12] have shown the two-learner problem using CSP on healthy patients, a gold standard technique in BCI which optimally maximises separability of two classes. As the user learns the system, the system learns the user, this causes a reduction in accuracy as there are two dynamic systems attempting to configure without any proper method. Bennet *et al* shows that with time, left and right MI becomes more localised and distinct but when there is no update to the projection matrix, accuracy declines from 0.88 to 0.60. However, when the feature space is updated in the third trial, accuracy followed 0.88 (trial 1), 0.98 (trial 3 – updated), to 0.86 (final trial). There is a significant increase in accuracy, and this improves reliability of the system for much longer than the no-adaption method. Therefore, the state-of-the-art shows two main issues: 1) automation of self-parameterization for dealing with non-stationarities, expert intervention, and reduced training; 2) cost reduction of a high-quality EEG recording system.

This paper presents a low cost, and portable EEG acquisition system, alongside a BCI system implementation which automatically adapts to non-stationarities in the signal thus allowing for longitudinal use in a plug and play fashion due to minimal training. This paper is structured as follows. Section II details the proposed systems for both EEG device and BCI model. The circuit is outlined with necessary components. The BCI model is shown from acquisition to output, with two parameter updating methods. Results using datasets from ALS patients are presented and discussed in Section III following by concluding remarks in Section IV.

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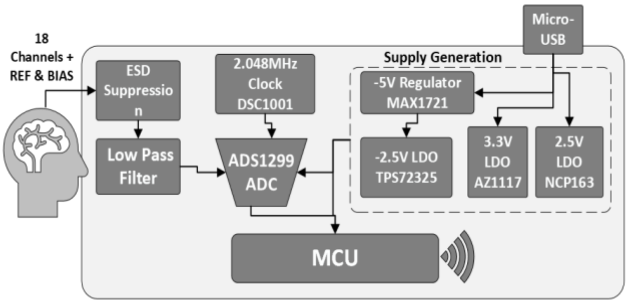

Fig. 2. Block diagram of the proposed BrainCard Hardware

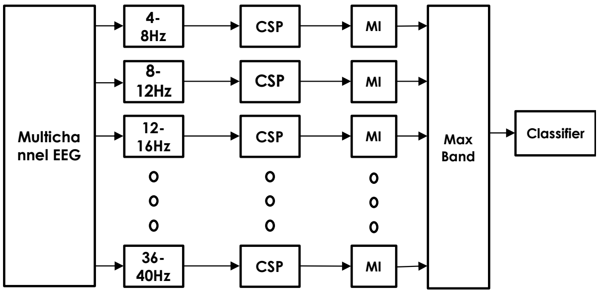

Fig. 3. Training model using FBCSP to obtain optimal bands and projection matrices

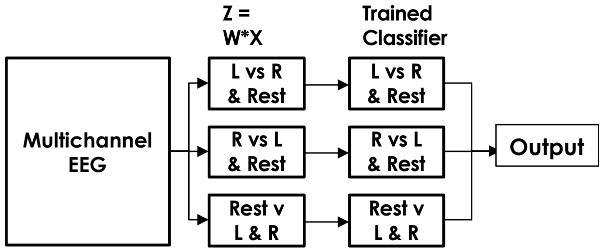

Fig. 4. Testing model using OVR approach, simulating online usage

Iteration	Total Data				
1	Train	Test			
2	Retrain		Test		
3	Retrain			Test	
4	Retrain				Test

Iteration	Total Data				
1	Train	Test			
2	Retrain		Test		
3		Retrain		Test	
4			Retrain		Test

Fig. 5. Cumulative (top) and Windowed (bottom) data retention method for updating feature space

II. Proposed System

The system consists of an EEG acquisition system (BrainCard) and a BCI model. The EEG collects data from 18 channels and can deliver the recorded signals to the machine learning model for decoding.

A. BrainCard Hardware

Fig. 2 illustrates the proposed schematic of the board which uses an analog, first-order RC filter to low pass at 1000 Hz along with a TVS diode (TI, TPD4E1B06) for ESD suppression. Following is the ADS1299-6 (TI) ADC daisy chained three times to result in a total channel count of 18 + reference and bias signal. Supply generation has an input of 5V from micro-USB and supplies a 2.5V (Onsemi, NCP163), 3.3V (Diodes Inc. AZ1117), -5V (Analog Devices, MAX1721) and -2.5V (TI, TPS72325). The clock running all three ADC's is a 2.048MHz (Microchip, DSC1001). An SPI bridge with the ability to connect to a processing/broadcasting unit, in this case the ESP32-C3-Mini-1 (Espressif), due to its low cost, size and ability to stream via Wi-Fi.

B. BCI Model

The dataset used in this study originates from [13], where recordings from three of the high-performing ALS patients are used. These patients completed four BCI sessions, involving 4 runs each, over the span of 1-2 months. The data acquisition process involved placing 19 electrodes on the patients' scalps, adhering to the 10-20 configuration, and using EOG electrodes to remove ocular artifacts. The acquired signals were amplified using a g.USBamp system, and the data was collected using a BCI software (BCI2000) and MATLAB.

The proposed offline BCI model is shown in Fig. 3 and 4 following a filter bank CSP approach where the EEG signal is filtered into multiple bands, and CSP is completed to maximize the separation between the two classes (in this implementation a one vs rest approach must be used as there are three classes). Extracting the optimal feature columns based on maximum mutual information between feature vectors and labels. The feature vectors are then used to train 3 classifiers, one for each action (Left/Right/Rest). The optimal bands and projection matrices are noted and only those bands are used to reduce redundancy in testing data. The projection matrix (W) is then used to convert raw EEG data (X) into the new feature space (Z) which can then be classified.

An important aspect of the proposed model is its ability to adapt to non-stationarities in the data. To account for this, the feature space is dynamically updated through retraining of the W using new correct data. In real-time scenarios, correct test trials can be utilized to retrain W and bridge the gap between outdated EEG data affected by non-stationarities and the new data. Fig. 5 depicts two means of achieving this where E is the optimizable length of data input for training and testing, as well as window length for determining optimal recent data for retraining. A linear discriminant analysis is used as the classifier which will separate the feature space. There is an inherent disadvantage to the cumulative approach where with time, data complexity increases. Overfitting is a notorious issue with CSP, therefore there with large amounts of data comes computational struggle and reduced accuracies. The solution to this issue is the introduction of windowed method, which keeps data retained constant, hedges against overfitting and should not increase computational load.

III. Results and Discussion

A. BrainCard

The fabricated device is shown in Fig. 6, split into the four sections mentioned. Measuring at 8.2 x 5.8 x 0.16 cm (approximately the size of a credit card), fabricated using a 4-layer, FR-4 board and a total manufacture cost of $275. Total

TABLE I. COMPARISON WITH POPULAR EEG ACQUISITION BOARDS

	Channel	Sampling Rate (Hz)	Size (mm)	Cost ($)	Battery Life (hours)	Weight (g)	Open Source
OpenBCI Cyton	16	125	61.2 x 61.2 x 1.6	1999	24	------	Yes
BEATS [14]	32	4000	90 x 56 x 82	400	24+	352	Yes
Emotiv Epoch	14	128	90 x 150 x 150	799	12	125	No
g.USBamp	16	38400	197 x 155 x 40	13000	10	1000	No
This work	**18-24***	**250-16000**	**82 x 58 x 1.6**	**275**	**24+**	**300**	**Yes**

*If the ADS1299-8 is used and not the 6 channel iteration in this work

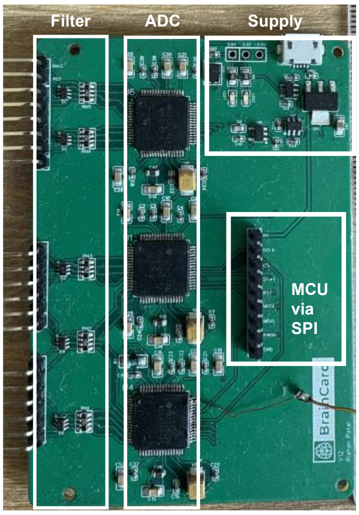

Fig. 6. Photograph of the fabricated prototype BrainCard with broken out SPI pins for changing processing unit

power consumption of the ADC's is measured at 20mA with the ESP32-C3-Mini-1 being rated to consume 350mA during the appropriate TX conditions for streaming. Assuming a 400mA usage, the device will be able to run for 25 hours using a 10Ah battery pack. Table 1 compares the proposed work against popular research grade devices, clearly demonstrating improvements in size, battery life and channel capacity. The desired frequency content is 4-40Hz as shown in Fig. 3, therefore using the minimum sampling frequency of 250Hz which should accompany 0.14-0.30uVrms (as per the datasheet) of input referred noise is optimal for achieving a high-quality EEG signal.

B. *BCI Model*

To evaluate the proposed model based on aforementioned data collected in [13], an optimization of parameters for both cumulative and windowed methods must be done to understand the impact of data size (E) and moving window on accuracies. It is ideal to have a lower E parameter as it leads to quicker start-up with a smaller initial training dataset. Fig. 7 illustrates the optimization process and performance of each subject's three classes with different E values. By using the optimal values, the E parameters for each subject were determined as 11, 12, and 15, indicating that as few as 6 left and right movements are required for training to achieve reasonably high testing performance.

Fig. 8 shows the achieved accuracies in each testing block, demonstrating consistent performance above 70% for most blocks, with a positive trend over time. However, the accuracy during the resting state remains significantly lower, as indicated by five tests falling below the desired threshold. It is

Cumulative	Left	Right	Rest	**Average Testing**	**Average Training**
S1	0.89	0.91	0.76	**0.85**	**0.97**
S2	0.70	0.69	0.68	**0.69**	**0.86**
S3	0.66	0.71	0.72	**0.70**	**0.92**

Windowed	Left	Right	Rest	**Average Testing**	**Average Training**
S1	0.84	0.78	0.83	**0.82**	**0.97**
S2	0.68	0.71	0.75	**0.71**	**0.87**
S3	0.70	0.70	0.80	**0.73**	**0.91**

Fig. 10. Cumulative (top) and Windowed (bottom) testing accuracies over three subjects and individual class. Windowed method performs marginally better than Cumulative.

important to note that as time progresses, the method experiences a gradual slowdown due to increased computational complexity and data storage demands. To address this issue, the implementation of the windowed method is proposed as a potential solution. For all models, it was found that the top 10 features, based on maximum mutual information, provide the best classification. While Subjects 2 and 3 did not achieve the 70% threshold, they were within a few percentage points of it. Further parameterization may be beneficial to reach the desired accuracies. On average, the three patients achieved 74% accuracy. It is worth mentioning that training accuracies consistently exceeded 90%, but showed a reduction over time due to excessive amounts of data that obscured the classifier's ability to separate classes. Thus, testing the windowing method, which is expected to maintain training accuracies.

During the windowed method, both the window length and E parameters were optimized. Subject 1, 2, and 3 were found to have optimal values of E = 16, 30, and 25, and Window Length = 21, 29, and 15, respectively. Employing this method resulted in higher accuracies on average for Subjects 2 and 3, with a slight reduction for Subject 1, while significantly relieving the computational load. In cumulative testing, batch 4 accumulated a session's worth of data (~260MB), whereas with windowing, only half of that data was used (~130MB). This reduction in data storage and computational load under the windowing method improved accuracy for two out of three subjects. Considering the challenges faced in achieving consistent accuracy across test blocks, it is evident from Fig. 9 that a resolution is required. To address this, we can draw upon the findings of Aliakbaryhosseinabadi *et al.* [10], who investigated electrode optimization in ALS patients for grasping and resting hand movement. Their study demonstrated that participant-specific parameter tuning resulted in accuracies exceeding 80% across 30 subjects. Furthermore, they found that using all 5 or just 1 channel showed no statistically significant difference, simplifying the setup, and reducing computational complexity. These findings

TABLE II. STATE OF THE ART BCI COMPARISON

Work	Offline Accuracies (%)	Online Accuracies (%)	Notes *Not adaptive models
[17]	83.3	83	Only 2/6 subjects completed online*.
[10]	80	N/A	MRCP feature not MI*
[15]	N/A	68.6	ERD based, mostly SCI patients
[16]	N/A	76	There is no clear pattern of improvement over time where three sessions are used. Healthy patients – BCI novice
This work	**92**	**75**	**1-2 months of assessment conducted on ALS patients with clear impact of auto-adaption over time. Online accuracy however is simulated.**

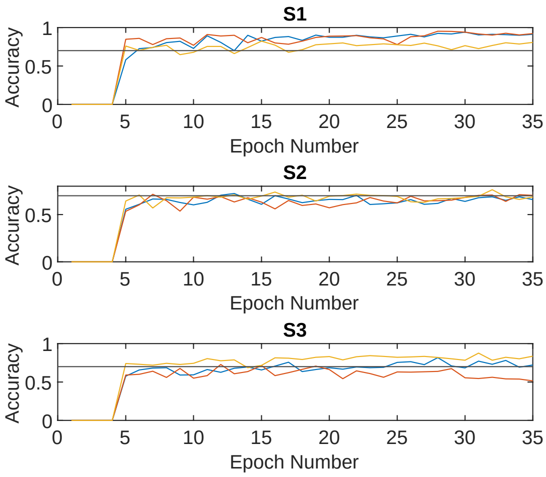

Fig. 7. Optimisation of E parameter in Cumulative mode of the model. Subject 1,2,3 and shown in order with the black line representing 70% minimum accuracy. Red, Blue and Yellow represent Left, Right, and Resting respectively. Optimal values are 11,12,15 for S1,2,3 respectively.

could potentially complement our implementation and improve the accuracy of our lagging test blocks.

Comparing the performance of our model against state-of-the-art online BCI systems in the literature proves challenging due to the limited availability of research and variations in methods employed for ALS. To shed light on this aspect, Table II provides a comparative analysis, showcasing how our model fares against both offline and online studies conducted with diverse end user groups. Notably, the scarcity of auto-adaptive models specifically designed for ALS patients further highlights the significance of our work. By employing gold-standard machine learning techniques, we not only improve upon existing approaches but also extend the analysis longitudinally. Our findings clearly demonstrate that the proposed method significantly enhances training performance and maintains robustness over extended periods of time, while achieving comparable testing results to those presented in [16]. It is important to emphasize that our study encompasses a comprehensive examination of EEG changes over a 2-month period with ALS patients, involving 16 runs, in contrast to the relatively shorter data they present.

IV. Conclusion

A portable EEG device called BrainCard has been presented, which, when coupled with an automatically adaptive BCI model, achieves highly accurate classification

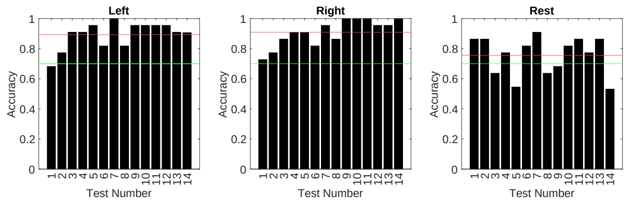

Fig. 8. Testing accuracies using Cumulative method for Subject 1 (highest performer). Green line shows the goal accuracies of 70%, and Red line shows average accuracy for this class. Optimal E = 11 where the Left, Right and Rest accuracy is 89%, 91% and 76% respectively.

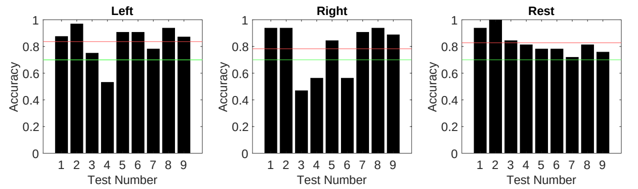

Fig. 9. Testing accuracies using Window method for Subject 1 (highest performer). Green line shows the goal accuracies of 70%, and Red line shows average accuracy for this class. Optimal E = 16 and Window Length = 21 where the Left, Right and Rest accuracy is 84%, 78% and 83% respectively.

of left, right, and resting state hand motor imagery in ALS patients. The device offers long operational duration, low cost, and versatility in processing options (cloud or host system). Table I demonstrates these advantages. Additionally, the proposed model exhibits potential for longitudinal use, maintaining high performance with automatic parameter tuning, reducing the need for expert recalibration. Future work includes hardware implementation, electrode optimization algorithms to reduce data complexity, and longitudinal assessments with ALS patients of declining ALSFRS scores to test robustness. A limitation of this work is the online testing needs to be validated with ALS patients in real time, which the other studies have done and this has not.

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References

[1] Arthur, K., Calvo, A., Price, T., et al. "Projected increase in amyotrophic lateral sclerosis from 2015 to 2040." Nature Communications, vol. 7, 12408, 2016.

[2] "Stages of amyotrophic lateral sclerosis (ALS) - Diseases," Muscular Dystrophy Association, https://www.mda.org/disease/amyotrophic-lateral-sclerosis/signs-and-symptoms/stages-of-als (accessed Jun. 21, 2023).

[3] M. Hamedi, S.-H. Salleh, and A. M. Noor, "Electroencephalographic motor imagery brain connectivity analysis for BCI: A Review," *Neural Computation*, vol. 28, no. 6, pp. 999–1041, 2016.

[4] A. Kubler *et al.*, "Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface," *Neurology*, vol. 64, no. 10, pp. 1775–1777, 2005.

[5] I. Lazarou, S. Nikolopoulos, P. C. Petrantonakis, I. Kompatsiaris, and M. 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*, vol. 12, 2018.

[6] O. Bai et al., "A high performance sensorimotor beta rhythm-based brain–computer interface associated with human natural motor behavior," *Journal of Neural Engineering*, vol. 5, no. 1, pp. 24–35, 2007.

[7] V. Peterson, C. Galván, H. Hernández, and R. Spies, "A feasibility study of a complete low-cost consumer-grade brain-computer interface system," *Heliyon*, vol. 6, no. 3, 2020.

[8] Y.-H. Liu, S. Huang, and Y.-D. Huang, "Motor imagery EEG classification for patients with amyotrophic lateral sclerosis using fractal dimension and Fisher's criterion-based channel selection," *Sensors*, vol. 17, no. 7, p. 1557, 2017.

[9] O. Bai, P. Lin, D. Huang, D.-Y. Fei, and M. K. Floeter, "Towards a user-friendly brain–computer interface: Initial tests in ALS and PLS patients," *Clinical Neurophysiology*, vol. 121, no. 8, pp. 1293–1303, 2010.

[10] S. Aliakbaryhosseinabadi *et al.*, "Participant-specific classifier tuning increases the performance of hand movement detection from EEG in patients with amyotrophic lateral sclerosis," *Journal of Neural Engineering*, vol. 18, no. 5, p. 056023, 2021.

[11] S. Saha *et al.*, "Progress in brain computer interface: Challenges and opportunities," *Frontiers in Systems Neuroscience*, vol. 15, 2021.

[12] J. D. Bennett, S. E. John, D. B. Grayden, and A. N. Burkitt, "A neurophysiological approach to spatial filter selection for adaptive brain–computer interfaces," *Journal of Neural Engineering*, vol. 18, no. 2, p. 026017, 2021.

[13] A. Geronimo, Z. Simmons, and S. J. Schiff, "Performance predictors of brain–computer interfaces in patients with amyotrophic lateral sclerosis," *Journal of Neural Engineering*, vol. 13, no. 2, p. 026002, 2016.

[14] B. Zou, Y. Zheng, M. Shen, Y. Luo, L. Li and L. Zhang, "BEATS: An Open-Source, High-Precision, Multi-Channel EEG Acquisition Tool System," in IEEE Transactions on Biomedical Circuits and Systems, vol. 16, no. 6, pp. 1287-1298, 2022.

[15] Faller J, Scherer R, Costa U, Opisso E, Medina J, *et al*. (2014) A Co-Adaptive Brain-Computer Interface for End Users with Severe Motor Impairment. PLoS ONE 9(7): e101168.

[16] J. Faller, C. Vidaurre, T. Solis-Escalante, C. Neuper, and R. Scherer, "Autocalibration and recurrent adaptation: Towards a plug and play online Erd-BCI," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 3, pp. 313–319, 2012. doi:10.1109/tnsre.2012.2189584

[17] O. Bai, P. Lin, D. Huang, D.-Y. Fei, and M. K. Floeter, "Towards a user-friendly brain–computer interface: Initial tests in ALS and PLS patients," *Clinical Neurophysiology*, vol. 121, no. 8, pp. 1293–1303, 2010. doi:10.1016/j.clinph.2010.02.157