Auto-Adaptive Model for Longitudinal Motor Imagery Decoding in Amyotrophic Lateral Sclerosis

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Abstract— **Amyotrophic Lateral Sclerosis (ALS) has been a grossly misrepresented end user group when developing coadaptive algorithms for Brain Computer Interfaces (BCI). Researchers have credited this issue to the difficulty of progressing disease in patients with ALS. This non-stationarity reduces accuracy over time. This paper introduces an online model, usable for a BCI using ALS patients data. The automatic coadaptive model effectively decodes 3 class motor imagery (MI) of the left, right hand and rest while adapting to address non-stationarities of EEG over time caused by various factors over the study duration. Adapting Filter bank Common Spatial Pattern (FBCSP) algorithm, where we show it could enable above 70% detection of hand MI in ALS end users longitudinally, previously lacking evidence. The evaluation results demonstrate that the model achieves average accuracies of 72.6% over a 1–2 month period of usage involving 8 ALS patients. This work shows the first auto-adaptive model with ALS patient EEG data providing a stronger incentive for further investigation by setting benchmark models on longitudinal datasets contributing to the solution of multiple challenges in this field.**

Keywords—adaptive, automatic, ALS, BCI, EEG, motor imagery

I. INTRODUCTION

ALS affects over 200,000 people globally, projected to increase by 69% by 2040 [1]. It's a progressive neuromuscular disease causing the gradual degradation of motor neurons, leading to paralysis and often death from respiratory failure within 2-5 years of onset [2]. Motor cortex neurons release action potentials during movement, measurable by EEG, but surface-EEG lacks spatial resolution. ALS patients can learn to modulate sensorimotor rhythms (SMR) associated with imagined movement [3, 4]. BCIs enable acquiring, conditioning, and decoding neural signals through machine learning for desired actions, offering functional assistance to ALS patients and preserving cognitive abilities. Training before the total locked-in stage is recommended [5] to reinforce motor imagery skills.

BCI limitations in clinical settings for ALS patients stem from EEG non-stationarities. Disease progression and declining motor function lead to cortical neuron reconfiguration, diminishing the SMR control signal [6]. Additional factors contributing to non-stationarity include mood, artifacts, and BCI illiteracy causing sub-70% accuracies [7]. Nihei et al. highlighted evidence of neuronal degeneration in the motor cortex of ALS patients, demonstrating a significant reduction in Betz cell density (3.9/mm2) compared to controls (8.8/mm2) [6]. Betz cell diameter and other areas with neurons showed a 58% reduction compared to healthy counterparts ($P<0.001$). These variations in signal, specifically ALS progression, cause covariate change in training and testing data resulting in a large reduction of prediction accuracy over time, especially when these devices should be used in a longitudinal fashion. Supplementary concerns are financial, and operational costs which need to be reduced by optimising electrodes, expert intervention, training, and portability [8-11]. Reducing the dependence on training these devices would provide higher utility in clinical settings where time is crucial whilst simultaneously enforcing the MI skill from early stages, benefiting clinicians, researchers, and patients alike.

Cutting-edge BCI research emphasizes the importance of regularizing parameter estimation within online systems [12], enhancing reliability and enabling uninterrupted usage. Adaptive techniques for feature space adaptation become crucial when training and testing data diverge, ensuring longitudinal usage and minimizing expert intervention [12]. Faller et al. conducted studies focusing on autocalibration and adaptation, highlighting success but emphasizing the need for improved performance in motor imagery challenges, particularly for individuals with ALS [13]. In a study with six SCI patients, they achieved a 69.5% accuracy rate in just five minutes using 16 electrodes, introducing a feedback loop for mutual learning [14]. Expanding to 22 SCI patients with a six-electrode coadaptive system, they reached a 68.6% accuracy rate, offering promising control without expert intervention and subject generalization [15]. Despite these remarkable advancements that push the boundaries of BCI technology, it is essential to note that all three of these studies, along with the rest of the literature share common limitation: the absence of longitudinal testing outside of the laboratory as well as a conspicuous gap in evidence concerning ALS patients, warranting further investigation. This is important, as we would like for this technology to be used for uninterrupted periods of time, without the need for experts, yet there is not enough evidence of success with ALS patients. Therefore, the state-of-the-art shows we need to test coadaptive models for dealing with non-stationarities like disease progression in ALS specifically which could also reduce expert intervention and training in real world, longitudinal usage. Working towards these goals, allows steps towards a better transition from a research tool, to a real world BCI that provides utility for ALS patients.

This paper introduces an online BCI model designed to automatically adapt to non-stationarities in the MI-EEG signal. This enables longitudinal usage in a plug-and-play manner with minimal training and intervention to accurately classify multiclass data. Our goal is to improve on established techniques to investigate the feasibility of addressing ALS-related non-stationarities over an extended period, an issue that lacks research in the literature of coadaptive BCI whilst setting benchmarks where it concerns ALS patient data in an automatically adaptive fashion. This paper is structured as follows. Section II details the proposed method for the model. The model is shown from acquisition to output, with two parameter updating methods. Results are presented and discussed in Section III following a conclusion in Section IV.

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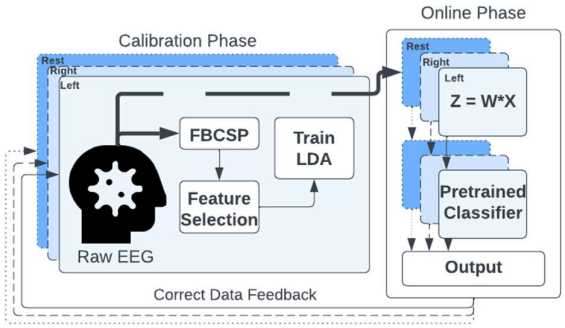

Fig. 1. Full system diagram using FBCSP to enable auto-coadaption of BCI in Calibration and Online phases with label feedback.

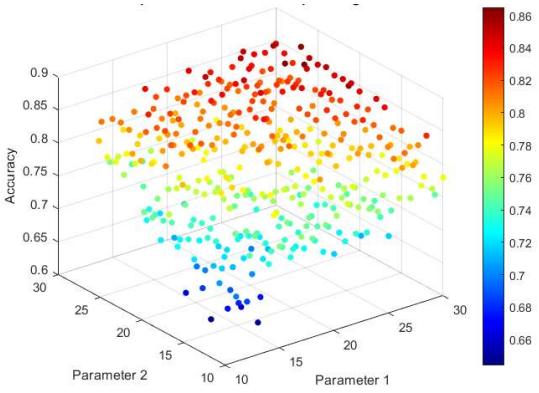

Fig. 2. Grid Optimisation of E (Parameter 1) and W (Parameter 2) in for Subject 9 to assess optimal values.

II. Proposed Model

The proposed BCI model is shown in Fig. 1 follows a FBCSP approach where the EEG signal is filtered into multiple bands, and CSP is completed to maximize the separation between the two classes (a one vs rest approach is 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 frequency bands and projection matrices are noted and only those bands are used to reduce redundancy in testing data. The projection matrix (obtained in the training phase) (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. There are two dimensions two this adaptation; updating the W and the classifier. We initially tested a cumulative, data retention method, appending correctly classified data to the training set for both adaptations. However, this approach proved computationally inefficient. To address this, we introduced windowing as an alternative. The cumulative method's increases data complexity over time, leading to overfitting issues with CSP. The windowed method maintains a constant sized data set, mitigating overfitting. To achieve adaptation, the correctly classified online trials are fed backwards, one by one. This simulates the online experience, where once the window is emptied, the W is retrained which bridges the gap between outdated EEG data affected by non-stationarities and the new

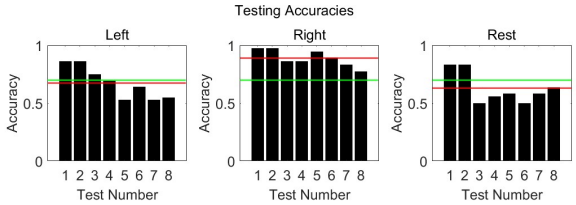

Fig. 3. Accuracies using a non-adaptive model for Subject 9 (highest performer). Test number represents each window, which moves through time. Green line shows the goal accuracies of 70%, and Red line shows average accuracy for this class. Optimal E = 18 and WL = 30 where the Left, Right and Rest accuracy is 68%, 89% and 63% respectively.

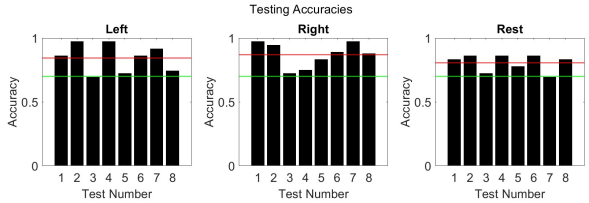

Fig. 4. Testing accuracies using automatic, adaptive model for Subject 9 (highest performer). E = 18, WL = 30 where the Left, Right and Rest average accuracy is 84%, 87% and 80% respectively.

data. Data size (E) is the optimizable length of data input for training and starting up the model, where the window length (WL) is for determining the amount of optimal data for updating parameters. A linear discriminant analysis is used as the classifier which will separate the feature space. The following will describe the adaptation in pseudocode: T_i is the batches of training data at I, Te_i is batches for testing at i, C_i is the set of correctly classified instances in Te_i and Tr_i is the updated training set, never exceeding size WL.

1	**repeat while** T_i **exists,** $i \leftarrow i + 1$
2	**if i = 1**
3	$T_1 = T_{1:E}$ and $Te_1 = T_{E+1:WL}$
4	**train** LDA(T_1) and **test** LDA(Te_i)
5	$Tr_1 = T_1 \cup C_1$ and **retrain** LDA(Tr_1)
6	**if i > 1**
7	$Te_i = Tr_i(end - WL{:}end)$ and **test** LDA(Te_i)
8	$Tr_i = Tr_i \cup C_i$ and **retrain** LDA(Tr_i)

III. Results and Discussion

A. ALS Dataset

Our study used data involving recordings from 8 ALS patients. Each patient completed four BCI sessions, with 4 runs and 10 trials per class, spanning 1-2 months. This totals 160 trials for each class. The data acquisition included placing 19 electrodes on the patients' scalps (10-20 configuration) and using EOG electrodes for artifact removal. Signals were amplified with a g.USBamp system, collected using BCI2000 software and MATLAB, and conducted under Penn State IRB, protocol *PRAMSO40647EP* under Dr Andrew Geronimo.

B. Performance Analysis

To evaluate the proposed model, optimizing windowing parameters (E and WL) is crucial. A lower E speeds up start-up with a smaller initial training set, impacting accuracies. Fig. 2 illustrates the grid optimization process and performance of Subject 9's average of three classes with

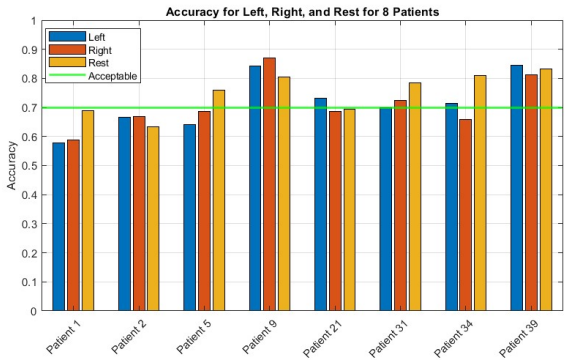

Fig. 5. Windowed total testing accuracies over all subjects and individual class. Average accuracies for each patient in order displayed are 61.7, 65.6, 69.5, 84.0, 70.4, 73.6, 72.8 and 83.0.

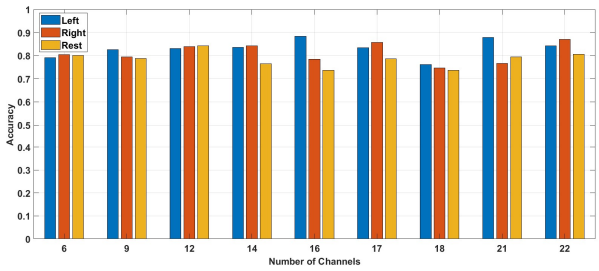

Fig. 6. Electrode optimisation using PCA for Subject 9 (High performer). Three classes are shown, where number of channels is varied from 6 to the full 22. Accuracies are shown to be very similar.

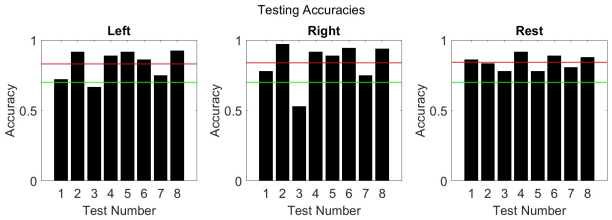

Fig. 7. Testing accuracies using Window method for Subject 9, post electrode optimisation. Using only 12 Channels, it is clear similar accuracies can be replicated to models using full 22.

different *E* and *WL* values. By using the optimal values, the *E* parameters for each subject kept below 20 motor imageries to enable reduced training times and *WL* values were ranging from 21 to 30 as was expected, larger amount of data for retraining enable better classification. Fig. 3 illustrates class accuracies per subject, using a standard FBCSP approach without updating W or the classifier where test numbers indicate each window that has been iterated through. It is very clearly shown that there is a decrease over time as we test newer windows. Alternatively, Fig. 4 displays the achieved accuracies in each testing block for Subject 9 with our adaptive model, demonstrating consistent performance above 70% for most blocks, and not reducing over time as Fig. 3 shows. We hypothesise the integration of mutual learning would enable improvements over time as opposed to the stagnation we see. For all models, it was found that the top 10 features, based on maximum mutual information, provide the best classification. While Subject 1 and 2 did not achieve the 70% threshold as seen in Fig. 5, they were within reasonable bounds (4-9%) of obtaining required levels. Further parameterization may be beneficial to reach the desired accuracies for lesser abled patients. On average, the eight patients achieved 72.6% accuracy. It is worth mentioning that training accuracies consistently exceeded 90%, especially with Windowed method as data is kept constant to reduce increased complexity.

Using the windowed method substantially reduced the computational load. In cumulative testing, test number 4 accumulated a session's data (~260MB), while windowing only utilized half of that data (~130MB). Considering the challenges faced in achieving consistent accuracy across test blocks, it is evident from Fig. 5 and 6 that a resolution would benefit overall and intersession accuracies. To address this, Aliakbaryhosseinabadi et al. [11] optimized electrodes for ALS patients, achieving over 80% accuracy across 30 subjects. Notably, using 1 or all 5 channels showed no significant difference, simplifying setup and reducing computational complexity. These findings may enhance accuracy in our lagging test blocks.

C. *Electrode Optimisation*

To achieve improvements in each test block, we used PCA for electrode selection, identifying top-performing electrodes based on channel variance thresholds (Fig. 6). Notably, maintaining a consistent 80% accuracy for each class with just 6 electrodes (originally 22) was observed for Subject 9. While not all subjects benefited, additional metrics are needed for a comprehensive cost-benefit analysis. For most users, reducing electrodes may slightly decrease overall accuracy but notably improves accuracy for lagging classes (Fig. 6, 12 vs. 22 channels). Fig. 6 also shows accuracy decrease with more data complexity, emphasizing the burden of excessive information. Though electrode optimization doesn't consistently enhance optimal accuracies, it's valuable for reducing complexity and setup requirements with minimal overall accuracy compromise. This suggests potential integration of more robust techniques to enhance the dataset. We hypothesize that introducing mutual learning will improve accuracies over time, to be tested in future online experiments. This strengthens the detection of distinct SMR signals, enhancing the BCI's command distinction ability. Aligned with prior literature, it emphasizes the activation of specific electrodes during MI, with crucial roles for contralateral electrodes. These findings impact BCI device development, emphasizing streamlined setups and minimized user inconvenience.

D. *Comparison to State of the Art*

Comparing our model to state-of-the-art online BCI systems for ALS poses challenges due to limited research availability and methodological variations. Table I offers a comparative analysis against diverse end-user groups, underscoring the scarcity of coadaptive models for ALS. Using the popular FBCSP techniques, we not only enhance existing approaches but also longitudinally analyse a different end-user group which clearly improves with our model as evidenced by Fig. 3. Our findings demonstrate improved performance and robustness over time, with testing results comparable to [14-19]. Notably, our multi-class (Left, Right and Rest classification) approach outperforms two class BCI's in complexity and utility while maintaining comparable accuracy.

In a primary study [16] conducted on the data used, the Revised ALS Functional Rating Scale (ALSFRS-R) showed no relationship with accuracies. However, attention-related tasks significantly correlated with MI quality. Age, a predictor

TABLE I. STATE OF THE ART BCI COMPARISON

Study	Online Accuracy (%)	End User	Length of online testing	Model
[14]	70.9	Tetraplegic - 6	1 Session - 200 Trials	LDA
[15]	68.6	SCI, MS, TBI – 15	1 Session - 144 Trials	CSP
[17]	69.5	Stroke - 6	18 Sessions – 2.5 Years	FBCSP
[18]	75.95	Stroke - 2	12 Sessions – Each with 32 Trials	2 Class Adaptive SVM
[19]	74.53	Stroke – 11	18 Session	2 Class CSP
This work	**72.6**	**ALS - 8**	**4 Sessions with 160 Trials – 1 to 2 Months**	**3 Class FBCSP**

of performance, revealed older patients perform better at P300 than MI, indicating younger patients have better SMR control. Notably, Patient 2 in the original study lacked defined SMR, but our model achieved above-chance accuracy (Fig. 5), evidencing steps towards success in inter-subject and inter-session differences for ALS patients.

IV. CONCLUSION

The proposed model exhibits potential for longitudinal use compared to non-adapting models like Fig. 3, maintaining high performance with automatic parameter tuning, reducing the need for expert recalibration. Our study contributes to the adaptive BCI field, integrating ALS patients over longer periods of time. Future work includes hardware implementation, further longitudinal assessments with ALS patients of declining ALSFRS scores to test robustness and finally some supplementary, data enhancing methods which can maintain higher scores over time. 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. Another limitation is we axiom that correct and incorrect trials can be identified. We believe in a real system, there are many modalities which can identify these from Error Related Potentials, to IMU's as shown in [20]. Finally, we have found that perhaps tracking Mutual Information of feature vector against correct label as our loss could be more informative to drive adaptation over time.

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