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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 Electroencephalography (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. ALS patients can learn to modulate specific frequency bands recognised as sensorimotor rhythms (SMR), these rhythms are associated with imagined or executed movement [3] which enables a useful control signal for a system. BCIs enable acquiring, conditioning, and decoding neural signals through machine learning for desired actions, potentially offering functional assistance to ALS patients, however to maintain this skill, training before the total locked-in stage is recommended [4].

BCI limitations in clinical settings for ALS patients stem from EEG non-stationarities. Disease progression and declining motor function lead to cortical reconfiguration, diminishing the SMR control signal [5]. Non-stationarity is something that affects all BCI users, where typically models need to be retrained upon every session [6]. 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) [5]. Betz cell diameter and other areas with neurons showed a 58% reduction compared to healthy counterparts. 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 could bear high utility in a longitudinal fashion [6]. Reducing the dependence on training and recalibration of these devices would provide higher utility in clinical settings where time spent training and retraining is crucial benefiting clinicians, researchers, and patients alike.

Cutting-edge BCI research emphasizes the importance of regularizing parameter estimation within online systems [7,8], 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 [8]. 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 [9]. 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 [10]. 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 [11]. 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 a common limitation: the lack of evidence for coadaptive algorithms in 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 in multi-session studies or analyses. 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 result in reduced expert intervention and simpler training in real world, longitudinal setting. 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.

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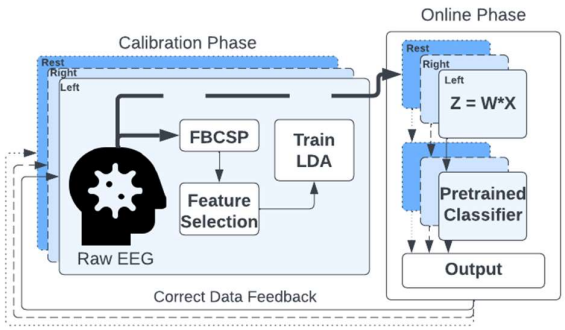

Fig. 1. Full system diagram using FBCSP to enable auto-coadaption of BCI in Calibration and Online phases with label feedback.

This paper introduces a BCI model designed to automatically adapt to non-stationarities in the MI-EEG signal. This show's evidence for up to 2 month BCI 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 by making them more practical in real world scenarios and to investigate the feasibility of addressing ALS-related, multi-session non-stationarities. An issue that lacks research in the literature of coadaptive BCI. Whilst additionally, establishing feasibility of the coadaptive BCI in ALS patient data. 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.

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 top 5 optimal feature columns based on maximum mutual information between feature vectors and labels. The feature vectors are then used to train 3 classifiers (with 10 fold cross validation to avoid overfitting), one for each class (Left/Right/Rest). The optimal frequency bands and projection matrices are stored 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 to 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 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 (LDA) is used as the classifier which will separate the feature space. The following will describe the adaptation in pseudocode where T_i is the batches of training data at i, Te_i is batches for testing, 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 [12]

Our study uses data involving recordings from 8 ALS patients, with an age range of 45.5 - 74, Revised ALS Functional Rating Scale (ALSFRS-R) score of 0 – 46 and time since symptom onset (TSSO) of 12-113 months whilst no disease progression was reported in the time-frame [12]. All of the metrics were obtained before the study began. Patients were enrolled from the Penn State Hershey Medical Center ALS Clinic where the criteria for inclusion were: (1) participants had to be at least 18 years old; (2) participants needed to have a confirmed diagnosis of ALS, categorized as definite, probable, probable with laboratory support, or possible according to the revised El Escorial research criteria. Individuals diagnosed with clinically significant dementia, as assessed by the neurologist at the ALS clinic, were excluded from the study. The data acquisition included placing 19 electrodes in the 10-20 configuration on the patients' scalps (FP1, FP2, F7, F3, FZ, F4, F8, T7, C3, CZ, C4, T8, P7, P3, PZ, P4, P8, O1, O2), with ground at FPz and referenced to linked earlobes. Three EOG electrodes for artifact removal with all impedances kept below 10kΩ. Signals were amplified with two g.USBamp system (g.tec GmbH), collected using BCI2000 software and MATLAB, and conducted under Penn State IRB, protocol *PRAMSO40647EP* under Dr Andrew Geronimo. A deeper dataset description can be found at [12].

Each patient completed four BCI sessions, with 4 runs and 10 trials of kinesthetic MI per class (left, right hand and rest), spanning 1-2 months. The patients went through a calibration run at the beginning of each session which follows a traditional approach of presenting left or right targets to cue MI or Rest. In the feedback runs, the patients were asked to imagine object-focused grasping to control left and right movement of a cursor which appeared in the center of the screen, to a target with continuous feedback from the movement of the cursor [12]. It is important to note the patients completed both a P300 and MI task in each session, however we will focus strictly on the MI data.

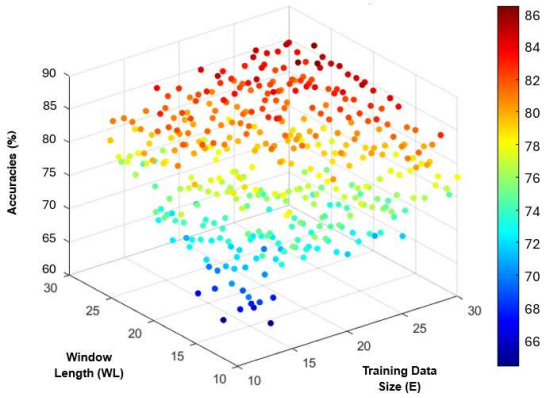

Fig. 2. Grid Optimisation of E and WL in for Subject 9 to assess optimal values.

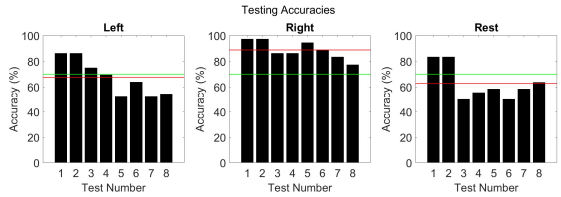

Fig. 3. Accuracies using a non-adaptive model for Subject 9 (highest performer). Test number represents each update period, which moves through time. Green line shows the goal accuracies of 70%, and Red line shows average accuracy for this class. Optimal E = 18 and WL = 30 where the Left, Right and Rest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

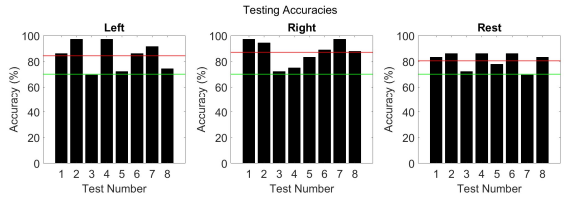

Fig. 4. Testing accuracies using automatic, adaptive model for Subject 9 (highest performer). E = 18, WL = 30 where the Left, Right and Rest average accuracy is 84%, 87% and 80% respectively.

Our dataset spans a duration of two months, comprising a total of 160 trials. This duration is comparable to the timeframe typically observed in the coadaptive BCI literature especially to encounter typical non-stationarities we wish to address. When contrasting our dataset with studies that do not utilize adaptive approaches, it becomes evident that the term 'longitudinal' aptly characterizes our specific dataset. By analyzing data over an extended period and incorporating adaptive techniques, we begin to capture longitudinal trends and changes in motor imagery decoding performance, thereby enhancing our understanding of BCI system adaptability over time and incorporating the ALS patient into this field of work.

B. Performance Analysis

To evaluate the proposed model, optimizing windowing parameters (*E* and *WL*) is crucial. A lower *E* speeds up training with a smaller initial training set (emulating the training required to begin using this device) but of course impacting accuracies. Fig. 2 illustrates the grid optimization process and

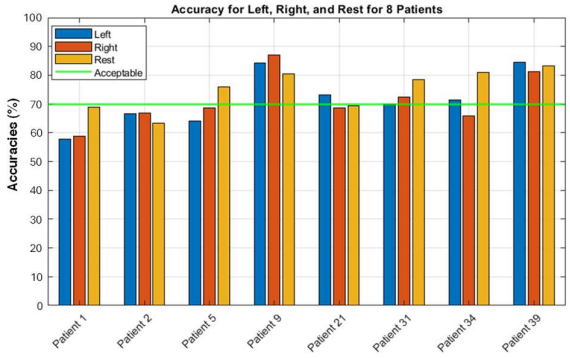

Fig. 5. Total testing accuracies over all subjects and individual class. Average accuracies for each patient in order displayed are 61.7, 65.6, 69.5, 84.0, 70.4, 73.6, 72.8 and 83.0.

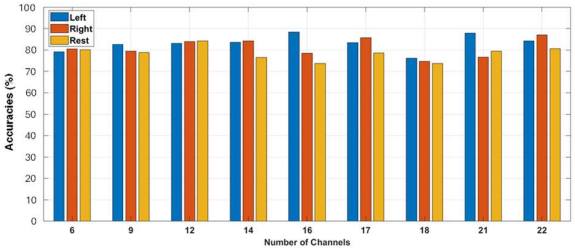

Fig. 6. Electrode optimisation using PCA for Subject 9 (High performer). Three classes are shown, where number of channels is varied from 6 to the full 22. Accuracies are shown to be very similar.

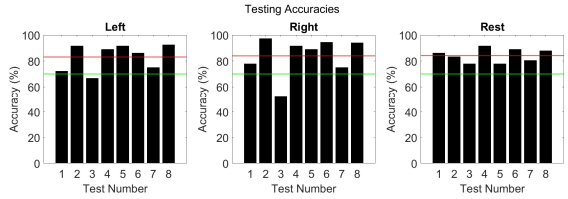

Fig. 7. Testing accuracies using Window method for Subject 9, post electrode optimisation. Using only 12 Channels, it is clear similar accuracies can be replicated to models using full 22.

performance of Subject 9's average of three classes with 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

TABLE I. STATE OF THE ART BCI COMPARISON

Study	Online Accuracy (%)	End User	Length of online testing	Model
[10]	70.9	Tetraplegic - 6	1 Session - 200 Trials	LDA
[11]	68.6	SCI, MS, TBI – 15	1 Session - 144 Trials	CSP
[13]	69.5	Stroke - 6	18 Sessions – 2.5 Years	FBCSP
[14]	75.95	Stroke - 2	12 Sessions – 384 Trials	2 Class Adaptive SVM
[15]	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**

patients achieved 72.6% accuracy. Our method employs a windowed data retention strategy, where the latest window of data is utilized to retrain the most recent model. This approach significantly reduces computational load compared to cumulative data retention methods. For instance, in cumulative testing, the accumulation of data for the fourth test session amounted to approximately 260MB, whereas windowing only required half of that, around 130MB. While cumulative data retention tends to yield higher accuracies over time due to the larger dataset available for model training, it also introduces a notable bias towards older data. In contrast, windowing circumvents this issue by focusing on the most recent window of data. By doing so, our method ensures that the classifier maintains a closer alignment with the feature space of both recent and current online data, thus mitigating bias towards outdated information. 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. [] 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 (Fig. 7), 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 undergoing the co-adaptive framework, underscoring the scarcity of coadaptive models for ALS. The studies compared in Table I are quite unique to each other in multiple ways.

Firstly, the compared end-user groups (SCI, tetraplegia, stroke, etc.) do not have progressive, degenerative elements, which reduces the complexity of models required to address non-stationarity. In contrast, our study demonstrates that even a challenging condition like ALS can benefit from coadaptation. It is crucial to emphasize the additional difficulty of developing models for ALS patients, which could ultimately lead to more robust and versatile models that are beneficial for all end-user groups, not just those with ALS.

Secondly, as shown in Table I, the duration of studies varies widely, from intra-session to inter-session adaptation (ranging from 1 to 18 sessions over timeframes of 1 day to 2.5 years). It is important to highlight that it is reasonable to consider a study relevant whether it involves one session lasting an entire day or five sessions each lasting 30 minutes across five weeks. The overarching common goal of all this research is to combat non-stationarity, which can be induced in various ways but ultimately allows us to address covariate shift. This shared objective justifies the comparisons made.

Using the popular FBCSP techniques, we not only enhance existing approaches by providing a framework for online, multi-class coadaptation by the updating Spatial Filter and Classifier. We also longitudinally analyse an end-user group who has been long overdue inclusion whilst shedding light on the potential benefits of Coadaptation which can only be seen inter-session. Coadaptive models show evidence for long term usage with ALS patients 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 ALSFRS-R showed no relationship with accuracies.

However, attention-related tasks significantly correlated with MI quality. Age, a predictor 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 clear 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, for the first time integrating ALS patients over longer periods of time. There are two dimensions of redundancy in this model: Filter banks which are not utilized by the model can be removed to improve processing speeds and the evidenced electrode reduction. 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 [Tao]. Finally, we have found that perhaps tracking Mutual Information of feature vector against correct label as an adaptation metric could be informative to drive more effective adaptation over time.

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References

[1] K. Arthur, A. Calvo, T. Price, 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] 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.

[4] 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.

[5] K. Nihei, A. C. McKee, and N. W. Kowall, "Patterns of neuronal degeneration in the motor cortex of amyotrophic lateral sclerosis patients," *Acta Neuropathologica*, vol. 86, pp. 55–64, 6 1993

[6] M. Arvaneh, C. Guan, K. K. Ang and C. Quek, "Optimizing Spatial Filters by Minimizing Within-Class Dissimilarities in Electroencephalogram-Based Brain–Computer Interface," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 24, no. 4, pp. 610-619, 2013, doi: 10.1109/TNNLS.2013.2239310

[7] 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.

[8] 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.

[9] 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

[10] J. Faller, T. Solis-Escalante, Ú. Costa, E. Opisso, J. Medina, Reinhold Scherer, G. Muller-Putz, "Online co-adaptive brain-computer interfacing: Preliminary results in individuals with spinal cord injury," IEEE 6th Int. Conference on Neural Engineering, pp. 977-980, 2013. doi: 10.1109/NER.2013.6696099

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

[12] 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.

[13] K. K. Ang and C. Guan, "EEG-Based Strategies to Detect Motor Imagery for Control and Rehabilitation," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 4, pp. 392-401, April 2017, doi: 10.1109/TNSRE.2016.2646763.

[14] E. Astrand, J. Plantin, S. Palmcrantz and J. Tidare, "EEG non-stationarity across multiple sessions during a Motor Imagery-BCI intervention: two post stroke case series," 2021 10th Internation.al IEEE/EMBS Conference on Neural Engineering (NER), Italy, 2021, pp. 817-821, doi: 10.1109/NER49283.2021.9441076.

[15] Z. Zhang, R. Foong, K. S. Phua, C. Wang and K. K. Ang, "Modeling EEG-based Motor Imagery with Session to Session Online Adaptation," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 2018, pp. 1988-1991, doi: 10.1109/EMBC.2018.8512706.

[16] T. Tao, Y. Jia, G. Xu, R. Liang, Q. Zhang, L. Chen, Y. Gao, R. Chen, X. Zheng, and Y. Yu, "Enhancement of motor imagery training efficiency by an online adaptive training paradigm integrated with error related potential," *Journal of Neural Engineering*, vol. 20, no. 1, p. 016029, Jan. 2023, doi: https://doi.org/10.1088/1741-2552/acb102.