Article

A Review of Online Classification Performance in Motor Imagery-based Brain-Computer Interfaces for Neurorehabilitation

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Abstract: Motor imagery(MI)-based Brain-Computer Interfaces (BCI) have shown increased potential for the rehabilitation of stroke patients; nonetheless, their implementation in clinical practice has been restricted due to their low accuracy performance. To date, although a lot of research has been made in benchmarking and highlighting the most valuable classification algorithms in BCI configurations, most of them are using offline data and not from real BCI performance during the closed-loop (or online) sessions. Since rehabilitation training relies on the availability of an accurate feedback system, we surveyed articles of current and past EEG-based BCI frameworks who report the online classification of the movement of two upper limbs in both healthy volunteers and stroke patients. We found that the recently developed Deep Learning methods do not outperform the traditional machine learning algorithms. In addition, patients and healthy subjects exhibit similar classification accuracy in current BCI configurations. Lastly, in terms of neurofeedback modality, Functional Electrical Stimulation (FES) yielded the best performance compared to non-FES systems.

Keywords: Brain-Computer Interfaces; Electroencephalogram; Motor-Imagery, Machine Learning; Deep Learning; Classification; Neurorehabilitation

1. Introduction

Worldwide stroke is a leading cause of adult long-term disability [1]. Growing evidence support that chronic stroke patients maintain brain plasticity, meaning that there is still potential for additional recovery of the impaired limb [2]. Various motor rehabilitation techniques have been developed, including motor training [3], mirror therapy [4], motor-imagery (MI) [5] and action-observation (AO) [6].

Presently, there is increasing evidence that motor-imagery practice combined with Brain-Computer Interfaces (MI-BCI's) in a closed-loop, could promote long-lasting improvements in motor function in chronic stroke patients [7–9]. Specifically, BCI's can act as an alternative non-muscular communication channel between the user's brain and a computer system for motor rehabilitation. MI is the cognitive process of imagining the movement of a body part without actually moving it [10]. Through MI, stroke rehabilitation effectively promotes structural and functional reorganization [11]. This is achieved due to the repeated recruitment of motor neurons circuit which repairs connections between damaged neurons, through neural plasticity, and eventually improving motor dysfunction [12].

The neurophysiological mechanisms underlying the MI practice reflect in sensorimotor rhythms (SMR), recorded through Electroencephalography (EEG) [13]. This type of rhythmic oscillations refers to the organized neural activity modulated by the MI and recorded over the sensorimotor cortex as decreases in the Alpha (8-12 Hz, also known as Mu rhythm) and Beta (13-26 Hz) frequency bands. When activity in a frequency band increases in response to stimuli, it is called event-related synchronization (ERS), while a decrease is called event-related desynchronization (ERD) [14].

The translation of the brain signals to the output of the BCI, as a neurofeedback, is accomplished through the distinct features aroused by the MI of different limbs. Traditionally, the classification involves a machine learning algorithm [15]. However, EEG signals pose processing challenges; since they exhibit low signal-to-noise ratio (SNR) and are prone to signal artefacts and external noise. Therefore, pre-processing is mandatory in order to remove electrical activity that is unrelated to the brain (i.e. heartbeats, eye blinking, tongue and muscle movements, electronic equipment and environmental noise). This notwithstanding, combined with the high dimensionality of EEG signals, interpretation, and classification of brain signals is a difficult task, with many of the approaches utilized suffering from poor classification accuracy. In addition, the training of the subject and the BCI system is usually prolonged, as most of the classification methods require a significant amount of data to predict the MI label accurately [16]. However, motivation and attention have an important influence on the emergence of distinguishable features for various MI tasks and the stability of EEG patterns. A monotonous MI-based BCI practice affects many times the engagement and concentration levels of the subjects, leading to a poor translation of the brain signals by the computer interface and a decline in the therapy effectiveness [17]. Consistent with this viewpoint, several studies have reported that feedback modalities of BCI system create a more immersive and motivating environment, which increases the embodiment of the user and thus, providing more robust EEG features [18]. Therefore, machine learning algorithms should adapt to non-stationary brain signals, while human learning approaches should assist in the production of more consistent EEG patterns for the user.

The feedback modalities used for BCI motor rehabilitation include; non-embodied simple two-dimensional graphics on a screen [19], embodied avatar representation of the patient on a screen or with Virtual Reality (VR) [20], functional electrical stimulation (FES) [21] or robotic exoskeletal movement [22]. In VR, the subject can perceive the imagined motor action, which could potentially activate mirror neurons that are also employed by mirror therapy for stroke rehabilitation [20]. The decoded brain oscillations are used to control a VR avatar which reproduces the imagined actions, most commonly between left and right-hand movement. This "closed-loop" feedback is presented in real-time, therefore the classification algorithm used should be fast, apart from accurate. Moreover, sensory feedback has been suggested to improve the induced neuroplasticity of post-stroke patients, by means of involving a greater part of the sensorimotor system (e.g. visual, auditory, haptic and tactile feedback) and evoking more distinguishable features [23].

During the process of identifying classification methods more suitable to the nature of EEG signals and due to the successful development of Deep Learning in different fields, like computer vision and speech analysis, many researchers were motivated to address the difficulties involved in classifying MI-EEG signals by employing Deep Learning. Unlike conventional machine learning approaches, Deep Learning can automatically learn complex individualized features from raw MI-EEG data using deep architecture, while eliminating the need for pre-processing and time-consuming feature extraction, since it can execute feature engineering by itself [24]. However, their disadvantages are also evident, since the large number of data is required, together with a large amount of hyperparameters which must be learned during training can increase the training time compared to other methods [25].

Another vital limitation of EEG-based BCI's is the variability across subjects. It is found that the discriminative information of EEG signals varies based on the basic characteristics (e.g., demographics, prior BCI experience) and psychological states (e.g., motivation, confidence and frustration) of the BCI users [26]. This phenomenon, combined with the need for minimizing the training and calibration time of the BCI system, leads to the use of transfer learning [27]. Transfer learning describes the procedure of using data solving one problem and applying it to a different but related problem. Transfer functions are employed so that the classification models can be adapted from the source domain to different target domains. However, the effectiveness of transfer learning strongly depends on how well-related the two subject-domains are [28].

Nonetheless, we cannot neglect the fact that stroke patients suffer from individualized lesions, which might evoke different EEG patterns. Therefore, current efforts might be

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directed towards adaptive models to tailor the individual use of the system [29]. In other words, the difficulty in reducing individual differences is to consider individual attributes comprehensively, and then to select some of the attributes that are effective for the system.

Although a lot of research has been devoted to identifying and comparing the best algorithm in offline BCI systems with healthy subjects, detailed information on which classifiers lead to the most accurate prediction of motor imagery is still missing in online BCI systems with post-stroke patients. It is still unclear whether the cortical lesions of post-stroke patients evoke discriminable EEG patterns for different body parts. Our perspective is that if both traditional and novel classification algorithms induce insufficient accuracy, then the features generated by the EEG MI signals of post-stroke patients might not be distinguishable. Overall, it is widely agreed that recovery may be promoted through contingent activation of efferent and afferent pathways. A good level of BCI accuracy is thus a prerequisite (otherwise there is no adequate contingency between the BCI command "efference" and the feedback). Thus, the main goal of this survey is to identify the current MI classification methods and highlight their limitations in BCI's for Neurorehabilitation.

In Section 2, we offer a brief summary of BCI pipeline and state-of-art methods, while in section 3 (Results) and 4 (Discussion) we will present and interpret the observations from our literature review, focusing on real-time EEG-based BCI in subjects performing MI of their upper limbs.

2. Motor Imagery Classification Pipelines

In this section, we provide a brief background in all the steps that are necessary in order to extract typical MI-related EEG features, and the different classifier algorithms.

2.1. Feature Extraction

EEG-based BCI's use data recorded from multiple EEG channels. A key problem when using multichannel data is the high computational costs and possibly poorer performance if feature selection is not used, due to the "curse-of-dimensionality" ([15]). The extracted features are able to capture salient signal characteristics which can be used as a basis for the differentiation between task-specific brain states.

During feature extraction, features are selected from the signals in either time domain or frequency domain. Band power features represent the power of EEG signals for a given frequency band averaged over a time window and time domain features are the combination of EEG signals from all channels [30]. The simplest frequency domain feature extraction method is Fast Fourier Transform (FFT). However, FFT does not take time information into account. An alternative approach is the Short-Time Fourier Transform (STFT) which divides the signal into multiple overlapping frames [31]. Nonetheless, the spectra obtained from FFT on short epochs have still poor resolution when compared to an Autoregressive model (AR) [31]. However, the validity of power spectra estimates depends on the selection of proper model order. Adaptive Autoregressive (AAR) model establishes the parameters of the model [32].

Nevertheless, the above two techniques, FFT and AR, uncover spectral characteristics of signals and do not obtain good performance with non-stationary EEG signals. Wavelet Transform (WT), in contrast, uses varying size windows such that high frequencies are evaluated on the shorter window and low frequencies over longer window [33]. Thus, WT performs better in time resolution of high frequencies as compared to STFT [30].

However, we cannot ignore that, in MI BCI, multichannel EEG recordings are used to discriminate the motor imagery patterns. Therefore, spatial filters have been used widely to extract spatial information from the signal. Common Spatial Pattern (CSP) generates spatial filters that minimize the variance of one class and maximize the variance of other classes simultaneously [34]. The CSP performance depends on the operational frequency band of EEG [28]. Therefore, several approaches have been proposed to fine-tune the subject-specific frequency range for CSP algorithm, such as Filter Bank Common Spatial Pattern (FBCSP) [35].

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2.2. Classification

After feature extraction, the signals are classified into various classes of the movement imagination. Most of the reviews in the literature have classified the classification methods into linear classifiers, non-linear classifiers, neural networks and deep neural networks [13], [15], [30]. The two main types of linear classifiers are Linear Discriminant Analysis (LDA) [36], [37], [38], [39], [40], [41] and Support Vector Machine (SVM) [21], [42], [43]. LDA has low computational requirements, however it might provide poor result on complex non-linear EEG data [30]. SVM overcomes this obstacle by using non-linear kernel functions to map the data into higher dimensional space [31]. Non-linear classifiers, on the other hand, are not as widespread and popular as linear classifiers and neural networks [44], [45]. Although k-Nearest Neighbour (k-NN) [46] and Bayesian classifiers [47] are generative and easy to implement, they are sensitive to irrelevant and redundant features [31].

An important upside of Artificial Neural Networks (ANN) is that they take into account the dynamic nature of EEG signal. They are assemblies of artificial neurons, arranged in layers, which can be used to approximate any nonlinear decision boundary. The Multi-Layer Perceptron (MLP) and the Gaussian classifier are the most used Neural Network architectures used in BCI research [48], [49]. In contrast to traditional neural networks, where weights have to be chosen carefully, deep learning approaches, like Convolutional Neural Networks (CNN) [50], [51] and Recurrent Neural Networks (RNN) [52], [53], have high descriptive power. Another benefit arising from deep learning is that it can be used to perform the whole pipeline of feature extraction, selection and classification within a single processing block. However, it should be noted that CNNs were adopted in EEG signals processing after first being established as a tool in image processing. Therefore, when using CNNs for the classification of MI EEG, pre-processing of the input data might be needed. Either raw data is fed into the CNN, and the first layers of the network are devoted to extracting spatial and temporal information or a time-frequency domain image is obtained from the data using STFT or WT [54], [55]. Finally, fuzzy classification is another computational intelligence approach used for EEG classification that has gained popularity, as EEG classification is a decision-making problem suited for fuzzy logic [33].

In this section, we describe our search criteria for this review, including the statistical tests used for the comparison.

2.3. Searching Criteria

The searching string utilized in Scopus database[1] (Elsevier, Amsterdam, Netherlands) consisted of the following format: TITLE-ABS-KEY ("brain computer interface" AND "motor imagery" AND stroke AND classification). The initial searching procedure yielded 138 results, however, our we applied a set of inclusion criteria to narrow further our search. Specifically, we selected a sub-set of papers which reported online accuracies (with new data from actual participants); originating from EEG-based MI-BCI's; and included two-class classification of upper limbs (left- and right-hand MI); reducing further the sample into 18 papers (Table 1). The exclusion criteria were: offline BCI studies; data not recorded by EEG (e.g. fNIRS); multi-class classification (three and above); two-class studies using data coming from MI of limbs apart from the two hands (e.g. feet, tongue, etc.); two-class studies classifying hand movement imagination and resting state; and studies using data from other BCI types, such as steady-state visual-evoked potentials or P300.

The features gathered from each paper were: 1) Author name; 2) Date of publication; 3) Classifier; 4) Type of classifier (e.g. traditional/ deep learning); 5) classification accuracy; 6) number of electrodes used; 7) number of subjects; 8) healthy or patients; 9) BCI protocol (number of sessions and trials); 10) feedback modality (e.g. screen, robot, etc.); and 11) average age of participants (Table 1).

[1] https://www.scopus.com

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Table 1. Summary of papers included into the review

Author	*Classifier*	*Performance*	*Feature Extraction*	*Number of Electrodes*	*Number of Subjects*	*Number of Sessions*	*Number of Trials*	*Feedback Modality*	*Participants*	*Years*
Herman [56]	T2FLS	69%	PSD	2	6	7	160	Screen	Healthy	-
Prasad [19]	T2FLS	69%	PSD	2	5	12	160	Screen	Patients	59
Pan [57]	QDA	67%	CSP+ AR	3	3	1	230	Screen	Healthy	-
Chen [36]	Autoencoder	74%	CSP	16	4	144	15	Screen+ FES	Patients	62
Xu [58]	LDA	86%	WT+ AR	2	8	3	40	Robotic	Healthy	27
Irimia [59]	LDA	95%	CSP	45	2	10	240	Screen+ FES	Patients	50
Zhao [60]	SVM	74%	CSP	41	5	1	40	Screen	Healthy	-
Irimia [61]	LDA	87%	CSP	64	5	18	160	Screen+ FES	Patients	60
Tayeb [62]	CNN	84%	FT	3	20	2	90	Robotic	Healthy	31
Karacsony [63]	CNN	72%	-	16	10	-	-	VR	Healthy	25
Vidaurre [64]	LDA	82%	CSP	64	15	1	300	Robotic	Healthy	-
Raza [65]	CNN	70%	CSP	12	10	1	120	Robotic	Patients	41
Mousavi [66]	LR	62%	CSP	64	12	1	180	Screen	Healthy	20
Benzy [67]	NB	68%	PLV	64	16	2	50	Screen	Patients	50
Achanccaray [21]	SVM	93%	CSP	16	20	-	-	VR+ FES	Healthy	26
Gaur [22]	LDA	80%	CSP	12	10	3	40	Robotic	Patients	41
Vasilyev [68]	NB	80%	CSP	30	11	6	-	Screen	Healthy	26
Zhang [16]	LDA	75%	WT+ AR	16	7	3	200	Screen	Patients	60

2.4. Statistical tests

For the evaluation of the correlation of a parameter with the classification performance of the BCI configuration we used the Pearson's correlation coefficient (r), while for comparing the classification performance of patients and healthy subjects or traditional machine learning methods and deep learning techniques we used a two-samples t-test. Finally, for identifying the influence of the various types of neurofeedback, an one-way ANOVA test was employed. The alpha value was set at 0.05 as a measure of significant levels.

3. Results

In this section, we present the classification accuracy of different ML algorithms and for different feature extraction methods. Moreover, we investigate the influence of non-ML factors, like user demographics (e.g. age), the user type (e.g. patient vs healthy), experimental setup (e.g. number of: trials, electrodes, subjects) on the BCI performance.

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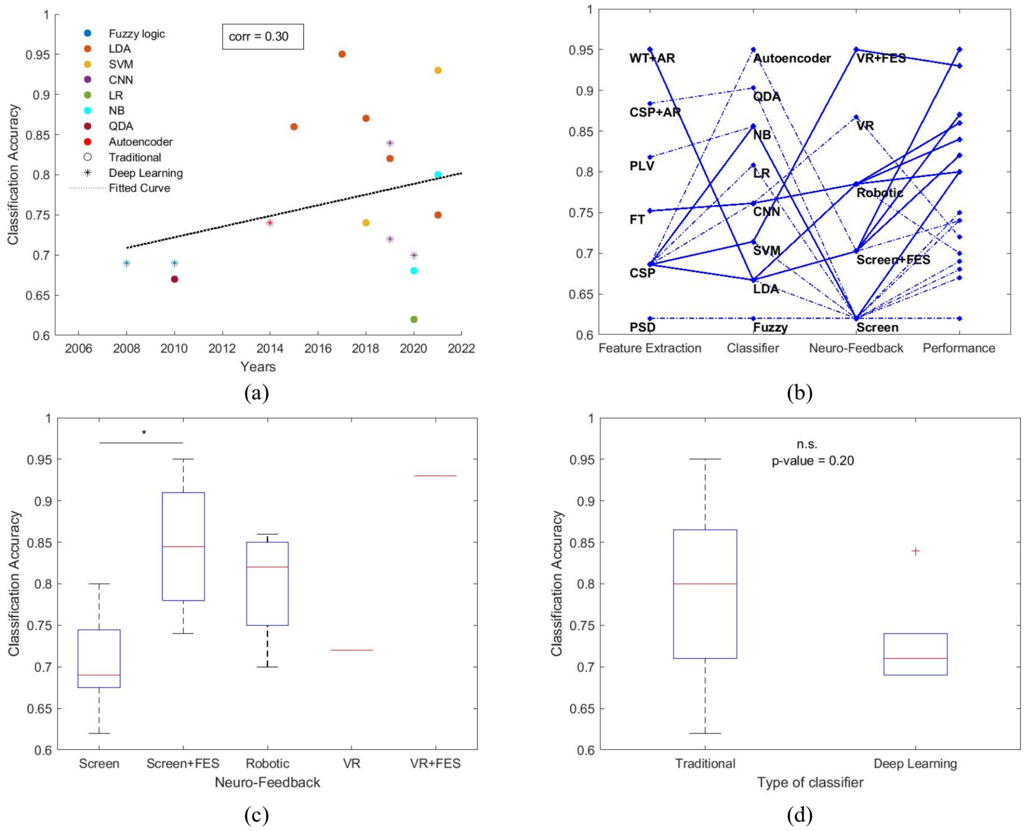

Figure 1. Feature Extraction, Classifier and neurofeedback influence on classification accuracy. a) Relation between classification accuracy and time. Each dot represents the average classification accuracy of a classifier stated with different colours depending the algorithm and different marker depending the type of classifier (traditional machine learning methods or deep learning). b) Feature extraction, Classification algorithm and neurofeedback relation with classification performance. Each line denotes the modalities used for each study. Solid lines represent the studies with classification accuracy above the average of all the papers included in the analysis (0.77), while dashed lines the algorithms with accuracy below the average. c) Comparison of the classification performance for different neurofeedback modalities. d) No statistical significant difference is identified between the traditional machine learning algorithms and the deep learning methods.

3.1. Comparison of the algorithms used for classifying Motor Imagery

Here, we focus on identifying features and classification algorithms which discriminate the imagination of upper limbs movements with the best performance.

According to the various studies surveyed, the classification performance ranges from 62% to 95%, with an average of 77% (Table 1). The majority of papers use CSP for extracting MI features that afterwards will be classified in most cases by LDA [58], [59], [61], [64], [22], [16]. The rest of the papers used either traditional machine learning methods, such as SVM [60], [21], Logistic Regression (LR) [66], Naïve Bayes (NB) [67], [68] and Quadratic Discriminant Analysis (QDA) [57], or Deep Learning techniques, like Type-2 Fuzzy Logic System (T2FLS) [56], [19], Convolutional Neural Networks (CNN) [62], [63], [65] and Autoencoder [19]. Further, Irimia et al. 2017 [59] and Anchancarray et al. 2021 [21] reported the best classification accuracy at 95% and 93%, while utilizing LDA and SVM, respectively. In both cases, the Feature Extraction method used was CSP. As illustrated in Figure 1(a), even though the correlation is not statistically significant, there is a positive trend of correlation for the classification performance over time ($r = 0.3, p = 0.23$).

Apart from the various classification methods utilized in the BCIs, it is important to investigate the features that are extracted from the EEG signal and the neurofeedback that is provided to subjects. In an attempt to discover if there is a particular BCI configuration that

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give rise to the best performance, we present the different Feature Extraction methods and types of neurofeedback with respect to the classification accuracy (Figure 1b). With solid blue lines, we present the BCI approaches that exceed the average classification accuracy (77%), while with dashed lines the BCI configurations that performed with a classification accuracy below the average.

In the literature, we discovered various Feature Extraction techniques, such as spatial filters; CSP was the most used and provided the most distinguishable features. The other methods used, are selecting the features either from the frequency domain; FT and Power Spectrum Density (PSD), or the time-frequency domain; WT and AR. Lastly, Benzy et al. 2020 [67] used Phase Locking Value (PLV) for discriminating the two-upper limb MI, while three other papers employed a combination of spatial and time-frequency domain Feature Extraction methods [57], [58], [16]. Although the results are not robust for the Feature Extraction and classification techniques, the neurofeedback modality provided to the subjects seems to have an important impact on the classification performance (Figure 1(b), 1(c)). We show that the quality of the neurofeedback during the BCI experiment has a vital role, since the BCI approaches using VR, Robotic Arm and/or FES have higher classification accuracy from BCI systems that employ only feedback via a computer screen. This result agrees with previous surveys which support that neurofeedback evokes more distinguishable features in the EEG signal [69], [70]. Nonetheless, only the group of Functional Electrical Stimulation (FES) has a statistically significant difference from the group of subjects that performed the BCI trials only with screen neurofeedback ($F(4, 13) = 4.74$, $p < 0.05$; Figure 1(c)). Finally, no statistically significant differences had been found between deep learning and traditional methods ($t(16) = 1.33$, $p = 0.2$; Figure 1(d)). Overall, we can observe that LDA performed satisfyingly on average, whenever it was employed.

3.2. Influence of user's characteristics to the BCI performance

BCI systems can also be affected by anthropogenic factors, thus, it is hard to make solid conclusions based only upon the limitations of the machine level.

So far, we examined the influence of different types of classifiers, feature extraction methods, and the impact of providing different feedback modality. Nonetheless, since our target is the applicability of BCIs in neurorehaiblitation, we accounted also for the user type, and specifically comparing the performance between healthy and patients. Previous research has revealed that EEG of patients is considerably different from signals recorded in healthy subjects [71]. In fact, it is not clear yet if post-stroke patients evoke distinguishable features from the imagination of upper limb movements. Hence, our survey included studies examining the classification accuracy in both patients and healthy. Contrary to our expectations, patients and healthy subject performed in a similar accuracy (Figure 2(a), $t(16) = 0.07$, $p = 0.94$).

In terms of the user's characteristics, we attempted to determine the effect of the subject's age on the BCI performance. Interestingly, the correlation of the user's age and BCI performance was almost zero (Figure 2(b), $r = -0.03$, $p = 0.91$). These results are inline with prior work of Blanco-Mora et al. 2022, where no statistically significant correlation was found between age and classifier performance [72]. However, we cannot neglect the negative trend that decline among the classification performance and the age of the subjetcs in each experiment.

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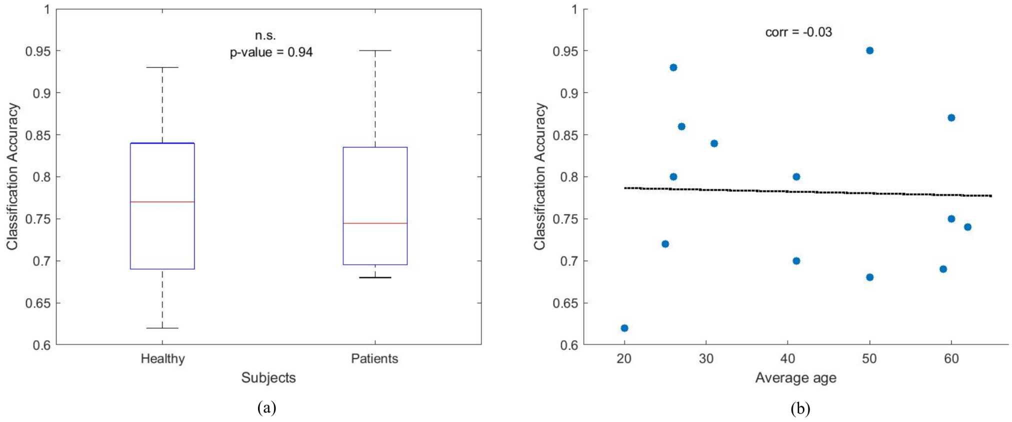

Figure 2. Impact of user's characteristics to the BCI performance a) No statistical significant difference is found between the classification performance between the Healthy and the Patients group. b) Relation between the average age of the subjects and the classification performance.

3.3. Correlation of classification accuracy with various parameters of BCI framework

Up to this point, our study is missing an evaluation of the BCI experimental protocol employed for each study. Therefore, we collected various parameters, such as the number of electrodes, the total number of trials (number of session * number of trials for each session) and the number of subjects that participated in each survey (Table 1). At this stage, it is important to provide some information about the presentation of these parameters. The number of electrodes reported in this review includes the electrodes that used in the Feature Extraction methods and not the recording process. Moreover, the total number of trials consists of both training and testing session.

Concerning the number of electrodes, no significant relationship was found with classification accuracy (Figure 3(a); $r = 0.05$, $p = 0.84$). According to the literature, there is contradictory evidence about the impact of the number of channels used and the classification performance. Although Meng et al. 2018 [73] found that subjects' average online BCI performance using a large EEG montage does not show significantly better performance than a smaller montage [73], Farquhar et al. 2013 [74] reported an effect when varying the number of electrodes used as features for the analysis [74].

Concerning the number of trials, and by extension the trials used for training the classifier, showed the highest correlation to the BCI performance (Figure 3(b)). Although the correlation of these two parameters is not statistically significant ($r = 0.38$, $p = 0.16$), we have to acknowledge the positive trend of interaction between the number of trials and the classification accuracy. In addition, it is important to mention that studies including post-stroke patients had more sessions, due to the neurorehabilitation longitudinal protocol.

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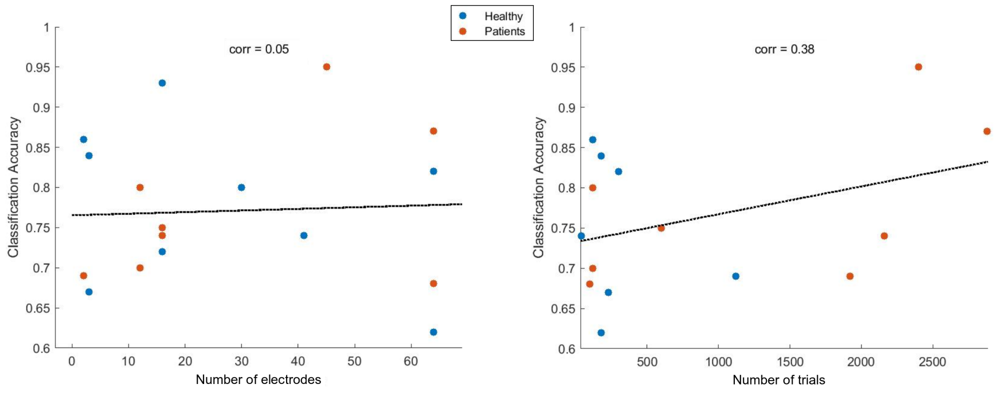

Figure 3. Effect of BCI system parameters to the classification accuracy relation between a) the number of electrodes, and b) the number of total trials used for the BCI training. The color of each point indicates if the data originates from healthy subjects (blue) or patients (red).

4. Discussion

Many of the classification methods surveyed in reviews are evaluated in offline BCI data [13], [75], [15], [25], [27], [28], [29], [30]. However, an actual BCI application is fundamentally online. Based on the papers surveyed in this manuscript, we attempted to identify some guidelines on whether to use various types of classification and Feature Extraction methods, neurofeedback modalities and BCI experimental parameters.

One of the major issue in MI-BCI research is to define the direction of future studies regarding the classification methods. Since the BCI pipeline is evolving rapidly and novel approaches such as Deep Learning and Transfer Learning are used for discriminating EEG signals more and more, one of our main concerns was if traditional and new approaches exhibit significant differences. According to our research, machine learning methods are not inferior to Deep Learning techniques. If we consider Deep Learning as an approach which is able to identify individualized separation rules for each subject, it would be logical to focus future work towards CNN and Recurrent Neural Networks (RNN). Nonetheless, the application of Transfer Learning in future studies seems more appealing, since traditional and novel classifiers perform in similar accuracy. In addition, patients and healthy subjects did not show significant differences in respect to the classification performance, therefore, the training of robust and powerful traditional classification methods in the healthy domain and the adaptation to each patient's domain might be the next pipeline that should be employed in online BCI systems.

Contrary to our results, Tayeb et al. 2019 [62] achieved better classification performance with Deep Learning models compared to traditional machine learning techniques, suggesting a route ahead for developing new robust techniques for EEG signal decoding. Tayeb et al. 2019 [62] was one of the few papers that attempted several classification methods with online data, however, in our research only the algorithm with the best performance from each paper is mentioned. Another important detail of the classification accuracy reported in our manuscript, is that in many cases where the BCI performance was presented along the neuro-rehabilitation period, we decided to outline the accuracy of the last week's sessions, since it was the value that the authors presented.

Apart from the significant variety of factors influencing the classification performance, mentioned in the Results section, we should not neglect the diverse ways of computing the classification performance in different studies. The usual way of calculating the classification performance in BCI systems is by training the algorithm with data deriving from several starting sessions and evaluate the performance based on the testing sessions. However, Irimia et al. 2017 [59], for instance, was training the classifier from data recorded during the first 4 runs of each session and testing the accuracy of the model in the last 2 runs of each session.

Future surveys, should include the clinical improvement of the patients and translate the impact of the classification accuracy to the clinical outcome. Unfortunately, this was impossible in this current version, since only three papers in our survey reported the clinical evaluation of the patients [19], [59], [61].

5. Limitations

Although this study collected and explored 138 EEG datasets, it was limited (N = 18). Our findings, therefore, have limited statistical power, and should be interpreted with caution. In addition, the statistical outcomes of our measurement and the comparisons presented here are exploratory and not confirmative.

Moreover, an important aspect of BCI configurations is to evaluate their clinical impact to the patients. However, not all studies report the clinical scale. In addition, even if the clinical scale is reported, different scale measures are used, which makes it difficult to relate the clinical outcome with the classification performance. Nonetheless, we tried to cluster the clinical outcome between improved and not improved patients, which yielded into 10 patients with reported improvement and 2 with stable conditions. Due to the unbalanced clustering of these studies, we decided not to further investigate possible relationships through correlations. Finally, so far we were not able to find studies with negative results nor reported non-improvements of patients after interventions.

6. Conclusion

In this survey, we have identified the EEG classification approaches that have been developed and evaluated in MI-based BCI systems using EEG recordings for the classification of upper limb movement. From existing data, we can see no significant differences in terms of classification accuracy between patients and healthy volunteers. This suggests that current BCI configurations used in rehabilitation, although not optimal, provide patients with modest benefits.

Regarding the parameters and demographics used in BCI configurations, we found that although there is a positive trend towards better classification accuracy over the years, no significant correlations are detectable. Moreover, in respect to neurofeedback modalities, FES yielded the best performance in both Screen and VR modalities compared to non-FES. Finally, in terms of the classifier's performance, we found that traditional methods (e.g. LDA, SVM, etc.) are still not surpassed by current Deep Learning methods.

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