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Yes/No Classification of EEG data from CLIS patients

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Abstract— **The goal of this research is to evaluate the usability of new features to classify EEG data from several completely locked-in patients (CLIS), and eventually build a more reliable communication system for them. Patients in such state are completely paralyzed, preventing them to be able to talk, but they retain their cognitive abilities.**

The data were obtained from four CLIS patients and recorded during an auditory paradigm task during which they were asked *yes/no* questions. Spectral measures such as the relative power of δ, θ, α, β and γ frequency bands, spectral edge frequencies (SEF50 and SEF95), complexity measure obtained from Poincaré plots and connectivity measures such as the imaginary part of coherency and the weighted Symbolic Mutual Information (wSMI) were used as features. The data was classified using Random Forest and Support Vector Machine, two methods successfully used to classify mental states in both healthy subjects and patients. Additionally, two cases were studied. The first case uses data recorded when the patient is answering questions, while in the second case it also includes data recorded when the experimenter is asking the questions.

The classification accuracy during training varies between 51.73 to 67.72% in the first case, and from 50.41 to 67.94% for the second case. Overall, wSMI with a time lag of 64 ms gave the best classification accuracy and in general, Random Forest appears to be the best classification method.

Clinical relevance **This case study investigates the usability of new features based on EEG complexity and connectivity to classify CLIS patients brain signal, what results in a further step toward the demand of more effective EEG-based Brain-Computer Interface communication systems for CLIS patients.**

I. INTRODUCTION

Communication is important for human beings, even more important for conscious patients unable to overtly express themselves. Locked-in syndrome (LIS) is one such state, in which the patient maintain his/her cognitive abilities, but is unable to voluntarily move his/her muscles, except for eye movements [1]. Despite the condition, patients report high quality of life, and it was found that higher quality of life correlates with their ability to communicate [2], [3]. Standard communication method uses eye movements and blinking, leading several research to build assistive devices depending on patients' eyes such as eye tracking or Steady State Visual Evoked Potential SSVEP-based brain-computer interfaces (BCIs). VEP has proven to be a faster way to communicate compared to other brain-computer interfaces usage [4]. The latter for example was used to evaluate covert attention in six locked-in syndrome patients. Two reached an offline accuracy above chance level, and one of them was able to communicate online [5].

Later however, LIS patients transition into a state in which the patient loses the ability to make any voluntary muscle movement. Even eye movements are lost, meaning that conventional assistive devices using eye movements are not usable anymore. This state is called completely locked-in syndrome (CLIS) [1]. This had lead research to use brain signals such as EEG and build EEG-based BCI as an alternative to communicate with patients. In [6], researchers introduced the "first EEG-based BCI system ever for communication with the completely locked-in patients" via mindBEAGLE. The system uses P300-ERPs or motor imagery (MI), in addition to three vibro-tactile stimulators to attempt communication with 9 LIS and 3 CLIS patients. 10 patients were able to achieve high accuracies, 9 were able to communicate with one of the designed paradigm, and 3 patients were able to communicate with the MI paradigm.

At this point it has been established that EEG could be use for a binary communication with completely locked-in syndrome patients. So far, the features used used are event-related potentials and frequency power of different frequency bands. In this study, features based on other spectral features such as the Spectral Edge Frequency (SEF), based on the signal complexity computed using Poincaré plots, and based on signal connectivity obtained with the imaginary part of coherency and the weighted Symbolic Mutual Information (wSMI) are used to classify EEG data recorded from CLIS patients. The data was obtained while they are performing the task of answering questions asked by an experimenter by thinking *yes* or *no*. The data and the experimental setup, as well as the signal pre-processing, features extraction and classification methods are described in Sec. II. The results are presented in Sec. III. This is followed by a discussion regarding the obtained results before concluding in Sec. IV.

II. TOOLS AND METHODS

This research aims at assessing the usability of new features and some chosen methods to classify EEG signals from CLIS patients. This section describes the data, measures used to extract features and classification methods. Signal pre-processing, segmentation, features extraction and statistical analysis were performed with MATLAB R2020a, the FieldTrip toolbox [7] and custom written scripts. Data classification was done using the statistical analysis software `R`. The package `doParallel` is used to accelerate computation.

A. Data description and pre-processing

1) Data description: The EEG data used here were obtained from 10 CLIS patients and recorded during an

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auditory paradigm task in which the patients were asked several questions that require a *yes* or *no* answer. The raw data acquisition was performed with BrainVision Recorder Professional (Brain Products GmbH). The answers to the questions are known by the family members and/or care-givers, and naturally by the patient. Fig. 1 illustrates how one session of recording is organized. It is composed of 20 trials corresponding to the 20 questions (10 *yes*, 10 *no*). Each trial starts with a rest period of 5 to 10 seconds, followed by the question (initiated by a trigger) and then a 15-second period in which the patient is attempting to answer the question by thinking *yes* or *no*. The experimental procedures involving human subjects described in this paper were approved by the Internal Review Board of the Medical Faculty of the University of Tübingen [8].

The questions are paired, meaning that for each question with a *yes* answer, there is a corresponding question that answers *no*. For example, for the question "Is Paris the capital of France?", which is true, the corresponding question would be for instance "Is London the capital of France?". Near Infrared Spectroscopy (NIRS) signals were also recorded during the experiment. More information about the patients can be found in [9].

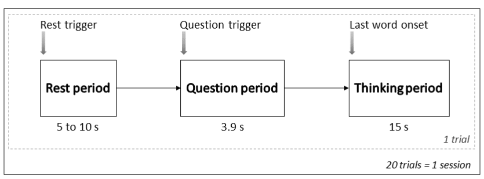

Fig. 1. Triggers description for one trial. One session is composed of 20 trials: 10 of them corresponding to the questions with *yes* answers and the other 10, to those with *no* answers.

2) Inclusion/Exclusion criteria: The EEG signals were recorded from different locations for each patient, and even for the same patient across time and also with different sampling frequency (200, 250 and 500 Hz). The experimenters did not divulge how they selected these values. The channels locations, however, were selected depending on the patient state at the time of the recording. To maintain a sense of uniformity, only the most common recording channels for the most patients were used in this study. The channels were FC5, FC1, FC6, CP5, CP1, CP6 according to the 10/20 system[10]. Four patients satisfy the channels criteria: Patients 1, 2, 4, 5 from the original dataset [9]. Another condition is the number of trials, which must be exactly 20 (as shown in Fig. 1). A session with less the 20 trials means that the experiment was halted due to patient's fatigue or some other reasons. Table I shows the number of data samples for each patient.

3) Signal pre-processing: EEG signals were filtered using a third order Butterworth bandpass filter with cut-off frequencies of 0.1 and 45 Hz.

B. Features extraction

The features used for classification are listed below and elaborated in more details in the following subsections:

- the relative power (RP) of the different canonical frequency bands: δ (0 - 4 Hz), θ (4 - 8 Hz), α (8 - 12 Hz), β (12 - 30 Hz) and γ (30 - 45 Hz) [11]
- the Spectral Edge Frequencies (SEF) at 50% and 95%
- the ratio SD1/SD2 of the short-term and long-term variability of the Poincaré plots
- the imaginary part of the coherency (iCOH), and
- the weighted Symbolic Mutual Information (wSMI) between all pairs of channels.

For each 1-second segment of each trial, RP, SEF, SD1/SD2 were calculated for each channel while iCOH and wSMI were computed for all pairs of channels.

1) Relative power: The relative powers of δ, θ, α, β and γ bands were calculated as the ratio of the total power in the frequency band and the total power from δ to γ (0.1 to 45 Hz) [12], [13]. For a signal $x(t)$, it is computed using (1).

$$RP = \frac{\int_{f_1}^{f_2} S_x(f)\,df}{\int_0^F S_x(f)\,df} \tag{1}$$

where f_1 and f_2 delimit the frequency band of interest. $F = 45Hz$ (upper frequency limit of the γ band) and $S_x(f)$ is the power spectral density of the signal $x(t)$ at the frequency f.

2) Spectral Edge Frequency: SEF is the highest frequency below which a certain fraction of the power of the signal is present. It is commonly used in sleep analysis and classification, and is expressed as SEF_r where r represents the fraction of the signal power for which the edge frequency is calculated [12], [13]. For a signal $x(t)$, it is computed using (2):

$$\int_0^{SEF_r} S_x(f)\,df = r\int_0^{Fs/2} S_x(f)\,df \tag{2}$$

where r equals 50% or 95% [12]. f is the frequency, and Fs represents the sampling frequency. SEF50 corresponds to the median frequency of the signal. Values of SEF50 and SEF95 were normalized by the Nyquist frequency so that they are always between 0 and 1.

3) Poincaré plots index: A Poincaré plot is a non-linear method to analyze the variability of time series. signals. Given the signal $x(t), t = 1...n$, it is constructed by plotting the EEG voltage at a specific time $x(k)$ on the x-axis and the EEG voltage $x(k+1)$ after a constant time delay on the y-axis. An optimum value of this time delay is 1/5 to 1/4 of the dominant cycle period [14]. For example, at a sampling rate of 256 Hz, a time delay value of 1 is equivalent to 4 ms.

Fig. 2 illustrates one Poincaré plot. SD2 represents the standard deviation of the points along the line of identity. SD1 is perpendicular to the line of identity [15]. The ratio SD1/SD2 (Poincaré index) is often used to evaluate the time series complexity [14].

$$SD1 = \frac{\sqrt{2}}{2}SD(x_n - x_{n+1}) \tag{3}$$

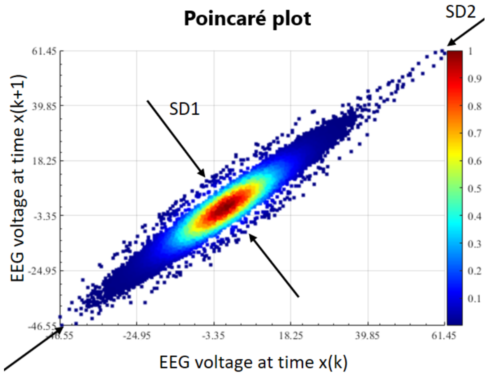

Fig. 2. Poincaré plot showing SD2 and SD1, the standard deviation of the points from the long axis (line of identity) and the short axis (perpendicular to the line of identity) respectively. A round oval pattern of the plot represents a random signal, while an elongated shape represents signals with linear features.

$$SD2 = \sqrt{2SD(x_n)^2 - \frac{1}{2}(x_n - x_{n+1})^2} \quad (4)$$

where SD is the standard deviation of the time series x_n.

4) Imaginary part of coherency: Coherency is a linear connectivity measure that assesses the relation between two signals x and y. Its value at a frequency f can be obtained using (5) [16].

$$C_{xy}(f) = \frac{S_{xy}(f)}{\sqrt{S_{xx}(f) \cdot S_{yy}(f)}} \quad (5)$$

where S_{xx} and S_{yy} are the individual power spectral density of x and y, and S_{xy} is the cross power spectral density of x and y at frequency f.

The coherency C_{xy} is a complex entity, and the use of only its imaginary part was introduced in [17] to reduce the effects of volume conduction in EEG signals and avoid false connectivity.

$$iCOH_{xy}(f) = \Im(C_{xy}(f)) \quad (6)$$

Quantitatively, its value ranges from -1 to +1. A higher value of coherence reflects an increased functional relationship between the two signals.

5) Weighted symbolic mutual information: Weighted Symbolic Mutual Information assesses both linear and non-linear functional connectivity between two signals, channels or brain regions x and y. It is calculated using (7). The EEG signal is first transformed into a sequence of discrete symbols $(\hat{x}, \hat{y})$ that are coded according to trends in amplitudes of k time samples separated by a temporal separation of elements τ [18]. In this research, $k = 3$ and $\tau = 4, 8, 64$ ms.

$$wSMI(x, y) = \frac{1}{\log(k!)} \sum_{\hat{x} \in \hat{X}} \sum_{\hat{y} \in \hat{Y}} w(\hat{x}, \hat{y}) p(\hat{x}, \hat{y}) \log(\frac{p(\hat{x}, \hat{y})}{p(\hat{x})p(\hat{y})}) \quad (7)$$

The value of wSMI equals 1 when the two signals are completely dependent, and zero if one signal is completely independent of the other.

6) Features extraction: The values obtained from each measure were averaged

- starting from the *Last word onset* until the end of the *Thinking period* (Case 1),
- starting from the *Question trigger* until the end of the *Thinking period* (Case 2),

to investigate if there were any difference in classification accuracy between both cases (cf. Fig. 1).

TABLE I
SAMPLES AND FEATURES DIMENSION

Patient	Samples	Features dimension (p)				
		RP	SEF50/95	iCOH	wSMI	SD1/SD2
P1	60	30	6	90	90	36
P2	540					
P4	700					
P5	580					

Table I shows the number of data samples for each patients, and also the features dimension for each measure. The column "Samples" represents the number of trials. Data from each patient have been arranged in a matrix in which the features were organized into p columns and each row represent data from each trial.

C. EEG classification

Data from each patient was subsequently classified using Random Forest and Support Vector Machines. The data was split into a 70/30 train/test sets. The train set was then partitioned into 5 groups of equal size. 4 groups were used to train, and the remaining group was used to evaluate the obtained model. This is repeated for all possible choices of held-out group, and repeated 2 times (5-fold cross-validation repeated 2 times). The performance score was obtained by averaging all performance runs [19], [20].

A random number generator was used so that the samples used during each training run was the same for all methods.

1) Random Forest: Random Forest uses decision trees to build its prediction models. At each split, a random sample of m predictors is chosen from the full set of p predictors, and the split can only use only one of these m predictors. In general, $m = \sqrt{p}$. This is done for each split and the overall prediction is obtain by choosing the class that occurs the most [21].

The `R` packages `randomForest` (denoted as `rf` later in this paper) and `ranger` were used to classify the data using Random Forest [22], [23]. The optimal number of trees for each algorithm was determined by manually setting different number of trees (23 values from 5 to 500) and choosing the number that produces the best performance.

2) Support Vector Machines: The `R` packages `caret`, `e1071` and `kernlab` were used to classify with Support Vector Machine (SVM). SVM is a classification method usually applied to a two-class setting. It is an extension of support vector classifier, which consist at using an hyper-plane to separate the two classes if the boundary between them is linear. SVM extends the support vector classifier by enlarging the feature space so that non-linear boundaries between classes are also taken into account. It uses kernels to do so [19], [24].

The kernel functions used in this research are:

Linear kernel:

$$K(x_i, x_{i'}) = \sum_{j=1}^{p} x_{ij} x_{i'j} \tag{8}$$

Polynomial kernel:

$$K(x_i, x_{i'}) = \left(1 + \sum_{j=1}^{p} x_{ij} x_{i'j}\right)^d \tag{9}$$

where d is a positive integer that represents the degree of the polynomial. The classification task was performed using degree values from 2 to 5.

Radial kernel:

$$K(x_i, x_{i'}) = exp\left(-\sigma \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2\right) \tag{10}$$

where σ is the inverse kernel width and its value was selected between 20 values from 0.0005 to 0.01.

For all SVM algorithms, the classification was done with different values of the cost C that was chosen from 20 values between 0.05 and 1.

3) Evaluation metrics: The performance of each classification method was evaluated using the classification accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where TP: True Positives, TN: True Negatives, FP: False Positives, FN: False Negatives.

D. Statistical analysis

Friedman's tests were performed to test the effects of starting point of the features averaging (Case 1 vs Case 2) on the classification accuracy [25]. The null hypothesis is that this starting point does not affect the classification accuracy against the alternative that is does. This is performed using MATLAB's `friedman` function.

III. RESULTS

The goal of this study is to assess the usability of new EEG features to classify data from CLIS patients into *yes/no* answers. The features used were the relative power of different frequency bands, spectral edge frequency, complexity measures via the Poincaré plots, and connectivity measures such as the imaginary part of the coherency and the weighted Symbolic Mutual Information. Different classification methods were also used: Random Forest implemented with the `R` packages `randomForest` and the `ranger`, as well as SVM with linear, polynomial and radial kernels. The classification task was performed on data extracted from the Last word onset (Case 1) and from the Question trigger (Case 2). Parameter tuning (number of trees for Random Forest, other parameters for SVM) was performed semi-automatically. The results reported here were obtained from classification methods with the highest train accuracy that also gave the best estimates on the test data.

1) Patient 1: In Case 1, the highest train (test) classification accuracy was achieved by applying Linear SVM to the relative power of the different frequency bands with 67.72% (72.22%). The most important variable for this classifier was the relative power in channel FC5 in the δ band. Patient 1 was the patient that achieved the highest classification accuracy among all patients.

Table II shows the classification accuracy for both Case 1 and Case 2 using SVM with a linear kernel. It indicates that the same algorithm does not yield similar results for both cases: an algorithm performing well on Case 1 does not necessarily mean that it will also perform well on Case 2. In Case 2, the best performance was achieved by applying Random Forest (`rf` with 10 trees) to the SEF95 feature with 67.94% (72.22%). The most important variable in this case was channel CP5.

TABLE II

SVM LINEAR KERNEL PERFORMANCE FOR PATIENT 1

	Case 1	Case 2
Train acc.	67.72%	64.75%
Test acc.	72.22%	38.89%
Sensitivity	66.67%	33.33%
Specificity	77.78%	44.44%
Precision	70%	40%
Recall	77.78%	44.44%

Random Forest methods performed better than the others on the connectivity measures as can be seen on Fig. 3, which illustrates the performance of the different classification methods for each selected feature for Patient 1 (Case 1).

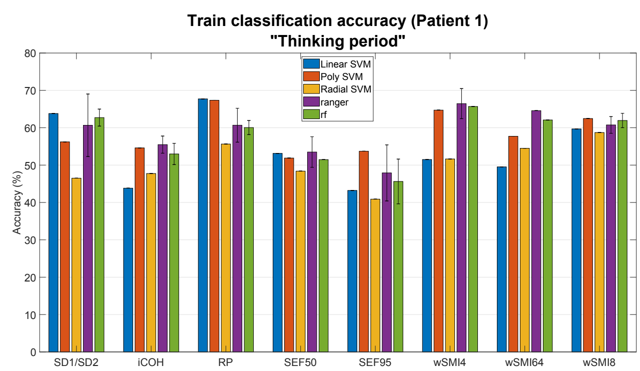

Fig. 3. Train classification accuracy of all features for Patient 1 (Case 1). The highest train accuracy was obtained using Random Forest (*ranger*) on the wSMI4 features. However, the classifier did not generalize well, leading to a test accuracy of 55.56%. A higher test accuracy of 72.22% was achieved using Random Forest *ranger* on the relative power, with a train accuracy of 67.72%.

2) Patient 2: For this patient, the highest classification accuracy for Case 1 was attained with wSMI64 using Random Forest `rf` with 7 trees with 58.64% (51.23%). With wSMI4, a higher test data accuracy of 53.7% (train accuracy: 53.7%)

was obtained with 8 trees. The most important variables for each case are the wSMI values between channels FC6 and CP5 in the β band, and channels FC1 and FC6 in the α band respectively.

For Case 2, classification with Random Forest `ranger` with 50 trees reached 57.3% (48.77%) with the wSMI4 features. But SVM with a polynomial kernel was able to achieve a 53.04% (50.62%) classification accuracy when applied to the iCOH. The most important channels are FC1 and FC5 in the β bands, and FC5 and CP1 in all frequency bands, respectively.

3) Patient 4: Patient 4 achieved the lowest train and test classification accuracy of all patients. For Case 1, the highest train accuracy was obtained using SVM with a polynomial kernel on the wSMI64 features: 52,96%, however the test accuracy only achieved 48.1%. A higher test accuracy of 52.38% was attained on the iCOH, with a train accuracy of 51.73%. The most important variable in the iCOH feature appear to be the connectivity value between channels FC5 and CP1 in all frequency bands. Fig. 4 represents the performance of all classification methods for each feature for this patient.

The feature with the highest train accuracy was also a connectivity feature for Case 2, this time with the wSMI64. The Random Forest `ranger` achieved a 50.41% (51.43%) accuracy, and the most important variable is the connectivity value between channels FC5 and CP6 in the α band.

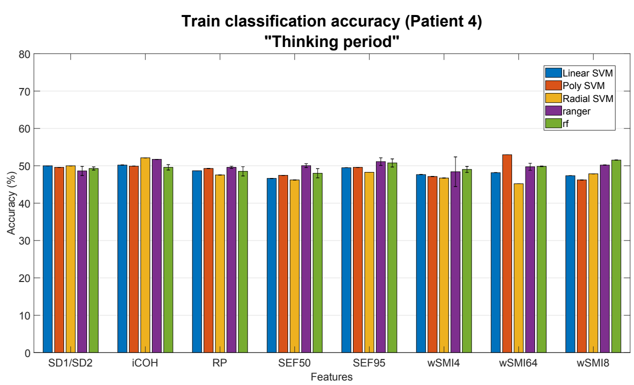

Fig. 4. Train classification accuracy of all features for Patient 4 (Case 1). For Patient 4, the train classification accuracy were relatively random.

4) Patient 5: The highest classification accuracy for Patient 5 was obtained with SVM with a polynomial kernel on the wSMI64 features: 57.99% (45.4%) for Case 1. The classifier's most important variable is the connectivity value between channels FC6 and CP5 in the α band. However, the method that generalizes better on the test data is Random Forest `ranger` applied to the wSMI64 features, attaining a train (test) accuracy of 53.34% (52.87%). The most important channels are the same as before, except that in this case, it is in the γ band.

For Case 2, an accuracy of 58.5% (45.4%) was achieved with Linear SVM on wSMI4. The connectivity value between channels FC1 and CP1 in the δ band came to be the most important variable. Anyhow, Random Forest `rf` performed better in the relative power, with a performance of 53.21% (54.02%). In this case, relative power of different frequency bands in channel FC6 was the most important variable.

5) Statistical analysis: To assess if the starting point of the EEG signal extraction effects the performance of each classification algorithm, Friedman's tests were performed on the classification results. The classification accuracy results were arranged to that the columns represent each case (Case 1 and Case 2) and each couple of rows represent the train and test accuracy for each classification method.

Table III shows the results of the significance tests. The low p-values of SEF95 ($p = 0.0377$) and wSMI8 ($p = 0.0229$) for Patient 1 indicate that the starting point of signal extraction (Case 1 vs Case 2) affects the performance of the classification algorithms. In those particular cases, the performance of the classifier is significantly higher in Case 2 compared to Case 1. For all the other cases and the other patients, however, the null hypothesis was rejected, meaning that the starting point of signal extraction did not affect the performance of the different classification methods.

TABLE III

STATISTICAL ANALYSIS RESULTS

	P1	**P2**	**P4**	**P5**
RP	0.1153	1	0.3817	0.4884
SEF50	0.5997	0.2888	0.8611	0.1573
SEF95	**0.0377**	0.0833	0.1656	0.2207
SD1/SD2	0.4795	1	1	0.2987
iCOH	0.2888	0.1659	0.8611	0.2207
wSMI4	0.729	0.2987	0.729	1
wSMI8	**0.0229**	0.5997	0.4884	0.729
wSMI64	0.3817	0.0833	0.1659	0.2987

IV. DISCUSSION AND CONCLUSION

Communication plays an important role in our every day life, more importantly in the lives of patients that are unable to overtly express themselves but are perfectly aware of their surroundings. This is the case of patients diagnosed with (completely) locked-in syndrome. In addition, it has been established that patients that are able to communicate report a higher quality of life. Previous studies that use EEG to build communication systems for CLIS patients are using ERPs or motor imagery. In this research, new features such as SEF, Poincaré index SD1 and SD2, imaginary part of coherence and wSMI were utilized to classify patients' EEG signals. The data were recorded during experiments as they attempt to answer *yes*/*no* questions. Random Forest and Support Vector Machine with linear, polynomial and radial kernels were used for the classification tasks.

Overall, despite its limited number of samples, Patient 1 showed the best classification accuracy results. Recording data from such patients is challenging since the feasibility of the recordings depend on the patient's health status and moral state. This explains the small number of samples for Patient 1 compared to the other patients. On the other hand, Patient 4 was the patient with largest number of samples, but also the lowest classification accuracy results. Increasing the number of cross-validation folds and repetitions during training did not change that. Patient 1 spent the longest time in ALS with 10 years, while Patient 2 and 4 spent 4 years in that state. In addition, while for the other patients, several years passed before they became completely paralyzed, Patient 4 became quadriplegic after only half a year [9]. The length of this period might be a contributing factor to the patients' poor performance.

The results of this research showcase that the most important variable depends on the method applied to the classify the data. In general, Random Forest appears to be the best classification method, especially when applied to connectivity measures. wSMI with time lag of $\tau = 16ms$ gave the best classification accuracy compared to the other time lags used. This may imply that trends in amplitude of the signals from the two channels of interest are more discriminating of the two classes for a longer time interval.

Statistical analysis results show that SEF95 and wSMI8 for Patient 1, the classifiers performances were affected by the point of data extraction: when the experimenter starts asking the question, or when the patient is instructed to answer it. Results show that the performance of the classifier is significantly higher in Case 2 compared to Case 1. This suggests that for these two cases, the patient's brain signals are activated from the time the experimenter starts asking the question.

In [6], 2 out of 3 CLIS patients were able to communicate using P300 potentials evoked by vibro-tactile stimulation and motor imaginary, with an accuracy of 20 to 100%. This shows, alongside the present study, that results can differ drastically between patients. On the other hand, despite having achieved the highest accuracy, Patient 1's performance are still not sufficient to obtain a reliable EEG-based brain-computer interface, which requires at least 70% of accuracy [26]. Furthermore, more data for training is needed, especially since wSMI seems to be a promising feature to be considered, in addition to investigating other binary classifiers.

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