Assessing the Impact of Idle State Type on the Identification of RGB Color Exposure for BCI

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Abstract: Self-paced Brain-Computer Interfaces (BCIs) are desirable for allowing the BCI's user to control a BCI without a cue to indicate him/her when to send a command or message. As a first step towards a self-paced color-based BCI, we assessed if a machine learning algorithm can learn to distinguish between primary color exposure and idle state. In this paper, we record and analyze the EEG signals from 18 subjects for assessing the feasibility of distinguishing between color exposure and idle states. Specifically, we compare separately the performances obtained in the classification of two different types of idle states (one relaxation-related and another attention-related) and color exposure. We characterize the signals using two different ways based on discrete wavelet transform and Empirical Mode Decomposition (EMD), respectively. We trained and tested two different classifiers, support vector machine (SVM) and random forest. The outcomes provide experimental evidence that a machine learning algorithm can distinguish between the two classes (exposure to primary colors and idle states), regardless of the kind of idle state analyzed. The more consistent outcomes were obtained using EMD-based features with accuracies of 92.3% and 91.6% (considering a break and an attention-related task as the idle states). Also, when we discard the epochs' onset the performances were 91.8% and 94.6%, respectively.

1 INTRODUCTION

EEG-based brain-computer interfaces (BCIs) can be seen as a pattern recognition system that learns from the users' brain signals for helping them to send messages and commands to the external world. In the beginning, these systems were focused only on disabled people but now, there are applications (as game controlling) for other subjects too. Particularly, EEG-based BCIs use one of 4 following neuroparadigms for sending the messages and commands: motor imagery (MI), slow cortical potentials (SCP), the P300 signals, steady-stable visual evoked potentials (SSVEP). The last two are visual BCIs that require an additional system for flickering the stimuli, which allows the generation of the specific signal for interacting with the BCI. In P300 BCIs, this flickering system helps the apparition of a p300 peak 300 ms after the desired output is flashed. Whereas in SSVEP BCIs, this system blinks all the commands but at different frequencies.

Targeting to discard this flickering stimulator, the use of the EEG responses to either color exposure (Åsly, 2019; Rasheed, 2011; Torres-García and Molinas, 2019; Åsly et al., 2019; Soler-Guevara et al., 2019) or the imagination of colors (Yu and Sim, 2016; Rasheed, 2011; Torres-García and Molinas, 2019) have been analyzed with different degree of successful aiming to implement a color-based BCI. Also, these works could take advantage of the presence of colors-based cues in our daily life.

Unlike the other visual BCIs, an online color-based BCIs will need a method for identifying the segments wherein the subjects are seeing the corresponding colors (control commands) and when they are not (idle state). In this case, the active status of a color-based BCI happens when the subjects see the target colors and the idle state happens when the subjects are in rest or doing a different activity. This makes that this kind of BCIs can be also grouped as self-paced BCIs.

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For that reason and looking for providing more evidence of the feasibility of a self-paced color-based BCI, we have analyzed if a machine learning algorithm can distinguish between the EEG segments of target colors (red, green and blue) and idle state using the dataset recorded in (Åsly, 2019). Particularly, the main contribution of this paper is the assessment of the impact of two different types of idle states on the recognition performance of color exposure and idle states. The first one (fixation cross) was related to the epochs wherein the subjects had to pay attention to the screen. Whereas, the second one was related to the indication for a short break. The relevance of this contribution is to look into if the method can recognize the activity of interest (EEG responses to color exposure) regardless of the kind of idle state analyzed. Finally, two different sets of features (EMD-based and DWT-based) along with two classifiers (Random forest and SVM) are studied for looking into if any difference can be found between the classification of each idle state (separately) and color exposure. Below, the most similar works are presented.

2 RELATED WORKS

The analysis of interest activities vs idle state is an important problem to be solved. In that sense, there are some works using motor imagery neuro-paradigm (Dyson, 2010; Dyson et al., 2010) and also using imagined speech (AlSaleh et al., 2018; Song and Sepulveda, 2014; Moctezuma et al., 2017). However, there is not enough evidence about if this could be achieved in color-exposure-based BCIs.

The work presented by (Moctezuma et al., 2017) evaluated the classification of linguistic activity vs linguistic inactivity (idle state). They used two different datasets, the first one consist of EEG signals from 27 subjects and 5 imagined words (internal pronunciation) and the second one with 20 subjects and 4 imagined words. The feature extraction was based on the discrete wavelet transform (DWT) with four levels of decomposition using the mother function biorthogonal 2.2, then for each sub-band extracted the teager, instantaneous, hierarchical and relative energy distributions were computed. They presented another characterization based on 15 statistical values. The obtained vectors were used as input for the random forest (RF) classifier, obtain accuracies up to 78% and 92% respectively for each dataset using features DWT-based and 83% and 91% when using statistical values.

The discrimination between imagined speech and two different non-speech tasks from EEG signals was analyzed by (AlSaleh et al., 2018). They applied high-pass and low-pass zero-phase filters in the range of 1–30 Hz for removing power line noise and noise corresponded to body movements. The features were extracted using spatio-spectral and temporal features from each EEG channel and it was used as input to the linear discriminant analysis (LDA) algorithm and Linear support vector machine (SVM). The results reported were obtained using a dataset from nine subjects 14 EEG channels.

They used 528 trials for each class and different trial length (1, 1.5 and 2 seconds). In their best case, they reported an accuracy of 67% for classification between imagined speech and visual attention (non-speech) using SVM and 1 second of the signal. Since the classification accuracy is near to the chance level, it shows that more work in the feature extraction is necessary, additionally, the paradigms comparison are not directly comparable with our approach.

The work described by (Åsly, 2019) presented a preliminary set of experiments for classifying the EEG signals corresponded to RGB colors and idle state, using a pre-processed version of the dataset recorder in (Rasheed, 2011). The dataset consisted of seven subjects and the configuration was using all the instances of all the subjects (a single dataset) for all the RGB color exposure as a single class and the idle state. Then, for each instance of RGB-color or idle state, the feature extraction was performed using the empirical mode decomposition (EMD), choosing only the first 3 intrinsic mode functions (IMFs). After that, for each IMF, the instantaneous and teager energy, Petrosian and Higuchi fractal dimensions, minimum, maximum, mean, median, variance, standard deviation, kurtosis, and skewness, were computed. The work reported accuracies up to 99% and 87% using the random forest classifier, while using the whole RGB-color segment or with a limited window (eliminating the first 500 ms for a possible P300 peak), respectively.

The onset of speech-related vs idle state was analyzed by (Song and Sepulveda, 2014), the dataset used consisted of EEG signals of linguistic activity from four subjects. They applied a ban-pass filter from 4-20 Hz, then an autoregressive model (AR) was used for feature extraction. The classification was performed using LDA, obtaining an accuracy of 79.88% on average for the four subjects.

The work presented by (Torres-García et al., 2019) shown accuracies up to 98.7% for classification of RGB-colors vs idle state, using SVM classifier. The previous results were obtained using a dataset of 7 subjects and 52 instances for each RGB color, the feature extraction consisted of sub-bands extraction using EMD and then for each sub-band 2 energy and 2 fractal features were computed.

Last, the most related works (described in (Torres-García et al., 2019; Åsly, 2019)) have analyzed the classification of color exposure and only one kind of idle state. Then, it is not clear if the performances can be kept analyzing another kind of idle state. Also, aiming at a wearable design based on dry electrodes, we assessed if the method can get similar performances to those gotten in previous works.

3 EXPERIMENTAL SET-UP

We recorded the EEG signals from 20 healthy subjects whose age range was between 21-27 years. Their EEG signals were recorded from eight electrodes using a g.Tec Nautilus device (with g.Sahara electrodes). The analyzed channel locations were FP1, FP2, AF3, AF4, P03, P04, O1 and O2, according to the 10-20 international system. These locations were selected based on related works (Yu and Sim, 2016; Rasheed and Marini, 2015; Liu and Hong, 2017).

All subjects signed an informed consent letter in which we clearly explained the research purpose, experiment-related risks and the management of the privacy of their personal data. Furthermore, they informed about BCI experience, their handedness and illnesses as color blindness and epilepsy. They responded to a simple questionnaire (more details in (Åsly, 2019)) regarding their mental and physical health before and after the experiment.

Before the subjects' arrival to the experimental session, they had to avoid both adding gel or any substance in their hair and consuming legal (coffee, tea, alcohol, medicines) or illegal stimulants at least a day before, and having a good rest during the previous night. Whereas before starting the experiment, the subjects' ears were cleaned using medical alcohol wipes (85%) for a better conductivity from the skin to ground and reference. Also, static electricity was discharged from them and the experimenter by touching a metal grounded object. Finally, the EEG cap was put on the subjects' heads while verifying the right electrode locations using a plastic measuring tape.

During the experiment, subjects were sitting in a comfortable chair and were indicated to follow the designed experimental protocol (described in subsection 3.1). Figure 1 shows the EEG signals recording following this protocol during the exposure to primary colors. Finally, subjects' were during the experiment in a dark room, which was free from audible and visible distractions. Also, an anti-static spray was applied to its floor and furniture, looking for getting high-quality recordings.

Figure 1: Subject in front of screen displaying RGB colors during the experiment.

3.1 Experimental Protocol

We designed an experimental protocol for recording the subjects' EEG signals during color exposure (see Figure 2). Specifically, we focused on the three primary colors (red, green and blue). Also, we recorded as a fourth event the responses to simple mathematical operations. However, those trials will not be discussed due as they are far from the aim of this description (see (Åsly, 2019) for more details).

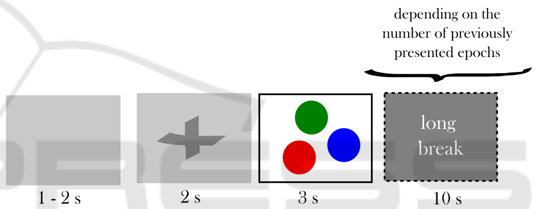

Figure 2: Protocol's timing for recording EEG signals during color exposure along with the duration for each shown screen.

The protocol's timing was decided to find a good trade-off between the dynamics of the eye, color perception and subjects' comfort. First, a gray screen was shown for a random time of 1-2 s. During this period, the subjects were allowed blinking. Then, this gray screen was kept but a fixation cross appeared in the screen's center to warn the subjects that a primary color would be shown 2 s later. Next, any color out of the three primary colors was randomly presented for 3 s and we asked the subjects to avoid blinks during this period as possible. The hexadecimal values of the used colors are shown in Table 1. Finally, a long pause of 10 s was shown depending on whether the number of presented epochs for each color reached the same multiple numbers of five.

Table 1: Used colors in hexadecimal format.

color	Hex value(RGB)
red	FF 00 00
green	00 80 00
blue	00 00 FF
light gray	C9 C9 C9
medium gray	80 80 80

3.2 Dataset Summary

At the end of the recording process, we obtained the EEG signals from 20 subjects. We recorded at least one run from all the subjects but we also got two runs for 13 subjects (S4-S11, S13-S16 and S19) and three runs for S20. We recorded 15 instances for each color, 60 for cross-fixation-related and 60 for break-related. The number of cross-fixation-related and break-related instances was that due to we recorded an additional class (mathematical operation), which is not analyzed in this paper.

After visual inspection, we rejected all the sessions of S4 and S8 due to these had either some channels without information or with artifacts. Also, the second session of S5 was rejected for the same reason.

Table 2: Available instances of the NTNU color exposure dataset.

Subjects	Colors	Cross	Break
S1-S3, S5, S12 and S17-S18	45	60	60
S6-S7, S9-S11, S13-S16 and S19	90	120	120
S20	135	180	180

Table 3: Instance distribution after pre-processing and amplitude-based epoch removal.

sub	R	G	B	break	cross
S1	13	14	12	46	51
S2	10	11	12	45	42
S3	8	6	6	44	39
S5	14	13	12	20	21
S6	22	26	26	34	21
S7	30	30	29	113	112
S9	27	26	27	50	109
S10	23	20	24	80	68
S11	28	29	27	73	80
S12	14	11	11	56	55
S13	25	24	23	98	95
S14	19	17	18	46	38
S15	29	30	30	108	103
S16	30	28	26	103	109
S17	13	15	13	10	36
S18	13	11	10	38	33
S19	27	27	29	114	115
S20	41	39	39	129	131

4 METHOD

4.1 Pre-processing

We applied the following preprocessing to the signals looking for both improving the signal-to-noise ratio of the EEG signals and rejecting artifacts related to any artificial trend in the signals, muscle movements, and blinks. First, we removed the mean of each channel. Later on, the signals were detrended and bandpass-filtered (2-30 Hz), then, these were epoched for extracting the interest segments of color exposure, pause-related and cross-fixation-related. This could be done due to the signals were *a priori* marked during their recording, so that an epoch is a repetition of the EEG signals recorded during the presentation of the interest colors, pause, and cross-fixation in this work. Then, those epochs with at least one sample with an amplitude higher/lower than $\pm 100\ \mu$ V were rejected. The final distribution of the instances for the experiments is shown in Table 3.

4.2 Feature Extraction

The EEG signals are non-stationary, which means that their frequency components are variable in time. Therefore, the most suitable techniques are those that allow the simultaneous analysis in both frequency and time for detecting changes in both domains. In this paper, we employed DWT and EMD, the first one allows the decomposition of the signals without the *a priori* definition of a constant window size that could avoid the detection of changes in some frequencies, such as Short-Time Fourier transform (STFT) needs to. Whereas, the second one is a data-driven method that does not depend on a dictionary of functions to decompose the original signals, unlike DWT and STFT. Also, DWT-based and EMD-based features have been previously explored in RGB color exposure classification. As to wavelet features, we based on the method described in (Torres-García and Molinas, 2019). Whereas, the computing of the EMD-based features is based on the method described in (Torres-García et al., 2019). Despite we analyzed a different dataset, the use of these methods also helps to have a benchmark for comparison purposes with these previous works.

For DWT-based features, we used the mother function biorthogonal 2.2 with 4 levels of decomposition. This number of decomposition levels was chosen due to it produces that each level is related to a given brain rhythm. Then, for each sub-band extracted, four features were computed: instantaneous and teager energy distribution, and Higuchi and Petrosian fractal dimension. After applying the previous process, each instance is represented by a feature vector with $8*5*4 = 160$ values. Those features were chosen because the previous results obtained and because those features can represent variations in both, amplitude and frequency (Didiot et al., 2010).

EMD was also used for sub-bands extraction, considering only the first three IMFs, in case only two

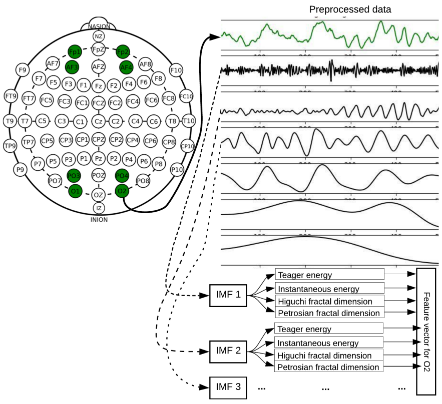

Figure 3: Method used for feature extraction from EEG signals recorded during exposure to colors and the idle states.

IMF were computed, we also used the residual. For each IMF we computed the same four features, with this process we obtained $8 * 3 * 4 = 96$ features per instance, as it is illustrated in Fig. 3.

The obtained vectors with their corresponding tags were used as input for two different machine learning classifiers, which are briefly described below.

4.3 Classification

From previous experiments (Torres-García et al., 2019; Torres-García and Molinas, 2019) in color exposure classification and in the discrimination of idle state and color recognition, we identified that SVM and RF are the most suitable classifiers for this task, outperforming to Naive Bayes and K-nearest neighbors. These classifiers aim to infer a function from the dataset characterized using any of the two kinds of features for classifying each instance from the dataset to any of both available classes (color exposure and idle state). Specifically, RF is an ensemble of decision trees with good properties as to speed and capability for handling instances with a large number of features it refers to. Whereas, SVM looks for the hyperplane that maximizes the separation between classes through the kernel trick. Finally, we used the versions of both classifiers implemented in the Weka toolbox (Witten et al., 2016) and using their default values hyperparameters. It is important to mention that since the number of instances is not significantly large, deep learning methods were not analyzed due to it is reported that their performance depends on a large amount of data, which is not common in BCI applications (Lotte et al., 2018).

5 EXPERIMENTS AND RESULTS

In this section, we investigated whether a machine learning algorithm could discriminate between all the RGB colors seen as a single class and the idle state (analyzing two different types of this, separately). All the experiments were carried out as binary classification problems and using balanced arrangements of the dataset depending on the number of instances of the minority class. Last aims to clearly evaluate if there is a kind of idle state that impact on the method's performance, and discarding the possible differences related to a different number of instances for each class.

All the classifiers' performances were obtained after the application of 10-fold cross-validation. It means that each dataset's arrangement is divided into 10 partitions, 9 out of them are used for training each classifier and one for separately testing them. For each classifier, this process is repeated until all the 10 partitions are used once for testing. The final accuracy for each classifier is averaged using the 10 accuracies for each testing partition.

5.1 Classification of Idle State and Color Exposure

In the first experiment, the epochs recorded during the break were assumed as the idle state. We then ran a binary classification scheme for each subject and using the same number of instances for each class. The number of instances for each subject was selected depending on the minority class. For example, S2 has 33 instances of all colors and 45 for the break. Therefore the experiment were carried out using 33 instances of both classes.

The performances obtained for all the subjects are shown in Table 4. For all of them, the performances were above the chance level for two classes. Besides, after applying sign tests [1] ($Z = 0.485$, $p = 0.628$, $\alpha = .05$) for DWT-based fts. and ($Z = 1.033$, $p = 0.302$, $\alpha = .05$) for EMD-based fts., it was observed that there is no difference between classifiers (SVM and RF) when the same type of features are analyzed. Nonetheless, there is a significant difference between the use of EMD-based and DWT-based features when we analyzed each classifier separately, ($Z = -3.535$, $p < .001$, $\alpha = .05$) for SVM and ($Z = -4.007$, $p < .001$, $\alpha = .05$) for RF.

In the second experiment, the epochs recorded during the cross-presentation screen were assumed as the idle state. We also ran a binary classification

[1] This test was chosen after the analysis of the outcomes' boxplots, which did not have a normal distribution and were not symmetric regarding the median.

Table 4: Percent accuracy and SDs obtained for the classifiers for the recognition of all the RGB colors and idle state (break).

subj	DWT-based features				EMD-based features			
	SVM		RF		SVM		RF	
	acc	std	acc	std	acc	std	acc	std
S01	79.5	6.6	82.1	13.7	88.6	12.5	85.7	9.7
S02	81.2	14.6	76.7	14.1	90.7	10.5	89.5	7.3
S03	75.0	26.4	75.0	23.6	87.5	17.7	90.0	17.5
S05	81.7	12.3	74.3	12.5	83.0	11.2	83.0	11.2
S06	83.4	8.3	87.9	4.7	94.4	8.0	91.6	7.0
S07	91.0	5.4	92.2	6.0	94.3	5.4	96.6	2.9
S09	94.6	5.2	91.5	4.4	98.5	3.2	96.9	4.0
S10	85.9	10.7	83.6	9.0	94.8	6.8	90.2	6.3
S11	83.5	5.3	85.4	8.4	91.8	5.2	92.4	7.7
S12	77.9	18.8	86.1	9.6	80.7	9.4	87.1	12.5
S13	87.3	11.1	83.2	11.2	92.2	8.6	91.6	8.7
S14	95.0	5.3	94.0	7.0	98.0	4.2	98.0	4.2
S15	90.5	4.5	89.9	6.3	97.2	3.9	94.4	6.5
S16	88.6	6.8	88.7	8.2	95.9	4.8	94.7	5.2
S17	86.3	9.5	82.3	6.3	92	10.3	84.3	8.3
S18	94.3	7.4	91.4	12.1	93.8	11.2	95.5	9.9
S19	89.7	6.6	90.2	6.8	92.7	6.3	92.7	5.8
S20	84.8	6.7	84.0	7.0	95.3	4.3	91.6	7.0
Avg	86.1	9.5	85.5	9.5	**92.3**	8.0	91.4	7.9

Table 5: Percent accuracy and SDs obtained for the classifiers for the recognition of all the RGB colors and idle state (fixation cross).

subj	DWT-based features				EMD-based features			
	SVM		RF		SVM		RF	
	acc	std	acc	std	acc	std	acc	std
S01	78.0	8.9	71.8	16.4	85.7	11.4	79.3	11
S02	71.0	13.6	75.2	19.3	80.5	11.4	77.4	14.4
S03	75.0	11.8	77.5	14.2	82.5	16.9	77.5	18.5
S05	81.7	12.3	65.0	9.5	90.0	14.1	70.0	7.0
S06	76.8	4.6	77.9	3.0	87.1	11.4	78.9	1.2
S07	78.7	8.7	78.7	8.6	97.2	3.0	88.2	4.2
S09	76.9	9.3	70.6	9.8	98.8	2.6	88.1	7.5
S10	82.1	7.9	75.5	8.3	91.1	4.6	86.6	9.1
S11	70.7	11.7	77.4	12.6	95.0	5.7	84.0	8.9
S12	69.5	10.9	69.3	21.3	85.7	15.1	76.4	16.1
S13	79.3	7.5	72.9	10.2	91.6	4.4	80.0	9.5
S14	73.8	12.0	78.0	14.8	91.2	11.5	83.6	8.0
S15	88.7	8.1	83.7	8.3	96.1	4.7	89.4	7.7
S16	79.2	9.3	75.1	10.2	97.7	3.0	89.4	8.2
S17	81.6	11.1	73.4	15.4	91.3	10.3	71.4	14.1
S18	71.7	18.8	74.5	12.1	96.9	6.6	79.3	15.6
S19	82.5	7.5	85.6	8.9	92.1	4.1	86.8	7.7
S20	82.4	10.5	79.4	7.0	98.7	2.0	89.0	5.9
Avg	77.8	10.3	75.6	11.7	**91.6**	7.9	82.0	9.7

scheme for each subject and using the same number of instances for each class (based on the minority class). For example, this number was set on 36 for S17.

The performances obtained for all the subjects are shown in Table 5. For all of them, the performances were also above the chance level for two classes. Also, there is no difference between classifiers (SVM and RF) when the average performances for DWT-based features are analyzed (after applying a sign test ($Z = 0.485$, $p = 0.628$, $\alpha = .05$)), but when the average performances for EMD-based features are analyzed there is a significant difference (after applying a sign test ($Z = 4.007$, $p < .001$, $\alpha = .05$)) between both classifiers, being better RF. Also, there is a significant difference between EMD-based and DWT-based features when the same classifier is separately analyzed. After the application of sign tests, we obtained ($Z = -4.007$, $p < .001$, $\alpha = .05$) for SVM and ($Z = -3.395$, $p < .001$, $\alpha = .05$) for RF, being better to use EMD-based features for both classifiers. Last, EMD-based features allowed a reduction in the average of the standard deviations for all the subjects.

5.1.1 Classification of Idle State and Color Exposure Removing the Epochs' Onset

Since the performances may have additional information related to the exposure to infrequent stimuli. Then, we discarded the initial half-second of each epoch, aiming to assess the impact of this in the experiments.

When we considered the epochs of breaks as idle states, we got the performances that are shown in Table 6. All the performances were above the chance level for two classes. In addition, after applying sign tests we observed that there is no difference between classifiers when either DWT-based and EMD-based features are separately used, ($Z = 0.250$, $p = 0.803$, $\alpha = .05$) for DWT-based features and ($Z = 0$, $p = 1$, $\alpha = .05$) for EMD-based features. However, the best average performances are gotten using EMD-features and RF. When we compared both types of features using the same classifier, significant differences were found after applying sign tests ($Z = -2.593$, $p \approx .009$, $\alpha = .05$) for SVM and ($Z = -2.750$, $p \approx .006$, $\alpha = .05$) for RF.

On the other hand, when we considered the epochs of the fixation cross as idle states, we got the performances showed in Table 7. All the performances were above the chance level for two classes. Unlike the above-mentioned comparisons between classifiers using separately the same kind of features, it was observed in Table 7 that there is a significant difference between classifiers after applying sign test ($Z = 2.1213$, $p \approx 0.033$, $\alpha = .05$) for DWT-based features and ($Z = 3.0641$, $p \approx 0.002$, $\alpha = .05$) for EMD-based features. For both types of features, the best performances were obtained using SVM.

Also, when each classifier is separately analyzed, it can be seen that there is a significant difference between both kind of features, after applying sign tests ($Z = -4.007$, $p < 0.001$, $\alpha = .05$) for SVM and ($Z = -3.395$, $p < 0.001$, $\alpha = .05$) for RF. This means that EMD-based also outperformed DWT-based features

Table 6: Percent accuracy and SDs obtained for the classifiers for the recognition of all the RGB colors and idle state (break) removing the epochs' onset.

subj	DWT-based features				EMD-based features			
	SVM		RF		SVM		RF	
	acc	std	acc	std	acc	std	acc	std
S01	85.9	12.8	86.1	7.1	89.6	10.5	93.6	6.8
S02	79.8	16.7	83.6	24.9	87.9	12.2	92.1	8.3
S03	72.5	21.9	80.0	19.7	87.5	13.2	87.5	17.7
S05	86.7	10.5	83.0	13.7	83.0	11.2	83.0	13.7
S06	91.6	8.0	89.8	6.7	92.6	5.8	89.8	7.0
S07	91.6	7.2	89.4	8.8	94.3	4.7	95.5	4.5
S09	93.1	4.4	93.1	4.4	94.6	5.2	95.4	4.0
S10	86.6	7.6	83.9	14.2	97.1	6.9	94.0	4.8
S11	89.1	6.8	89.8	7.8	91.7	4.3	94.2	5.7
S12	81.8	13.3	87.5	10.0	83.2	10.9	90.2	15.1
S13	86.8	6.2	85.9	10.2	91.6	9.8	91.5	6.6
S14	92.0	6.3	95.0	7.1	98.0	4.2	94.0	8.4
S15	95.6	4.4	92.1	6.0	97.2	4.7	94.9	4.2
S16	89.8	7.5	89.2	7.5	94.6	3.5	94.0	4.1
S17	88.0	14.0	90.0	10.5	92.0	10.3	92.0	10.3
S18	95.7	6.9	95.7	6.9	92.4	11.3	95.5	7.3
S19	92.8	5.4	90.9	5.3	90.3	5.1	95.1	4.9
S20	91.6	8.2	86.5	9.9	95.3	5.9	92.4	8.5
Avg	88.4	9.3	88.4	10.0	91.8	7.8	**92.5**	7.9

Table 7: Percent accuracy and SDs obtained for the classifiers for the recognition of all the RGB colors and idle state (fixation cross) removing the epochs' onset.

subj	DWT-based features				EMD-based features			
	SVM		RF		SVM		RF	
	acc	std	acc	std	acc	std	acc	std
S01	78.6	15.5	79.3	12.9	87.1	8.4	87.3	10.2
S02	65.2	17.7	80.7	15.5	86.4	10.7	79.1	15.0
S03	82.5	16.9	67.5	20.6	95.0	10.5	80.0	19.7
S05	80.0	15.3	73.3	8.6	88.3	13.7	78.3	11.3
S06	80.9	7.2	77.9	3.0	91.7	8.3	77.9	3.0
S07	90.5	8.7	84.2	7.1	98.9	2.3	94.4	3.7
S09	87.5	8.8	79.4	7.3	98.8	2.6	95.0	4.9
S10	88.1	7.8	73.3	14.5	98.5	3.1	93.2	7.5
S11	87.8	9.6	82.3	11.1	97.5	4.3	92.7	7.6
S12	76.6	16.6	74.6	13.5	97.1	6.0	85.2	12.8
S13	87.6	9.1	82.7	5.9	96.6	3.6	88.3	8.9
S14	71.7	17.3	78.3	12.6	87.8	13.3	90.1	11.0
S15	88.3	9.2	82.5	11.8	96.7	3.9	83.8	8.0
S16	84.6	10.6	82.1	7.4	97.6	4.2	94.0	4.9
S17	81.8	14.3	73.8	16.8	96.3	6.0	85.9	16.1
S18	78.1	13.7	75.0	19.2	94.3	13.8	91.4	10.0
S19	79.0	13.2	84.9	10.4	95.8	4.2	86.7	10.0
S20	84.0	8.8	83.2	10.1	98.8	2.8	92.8	6.1
Avg	81.8	12.2	78.6	11.6	**94.6**	6.8	87.6	9.5

for this kind of idle state. Furthermore, the method obtained lower standard deviations when EMD-based features are analyzed.

On the other hand, since SVM and EMD-based features got the best accuracies, we applied an additional sign test to the accuracies obtained for both kind of idle states (relax-related and attention-related), showing that there is not a significant difference between both ($Z = 1.65$, $p = 0.099$, $\alpha = .05$). This suggests that exposure to primary colors is different from the two idle states analyzed, and a method could be designed to take advantage of this fact for implementing a self-paced BCI.

Finally, despite all the averaged accuracies obtained removing the epochs' initial half-second were better than the whole epochs were used, when we separately analyzed the best outcomes for each kind of idle states (using SVM and EMD-based features) the differences were not significant. Sign tests were applied for both kind of idle states with and without the initial half-second, getting ($Z = 1.206$, $p = 0.228$, $\alpha = .05$) for break-related idle state and ($Z = -1.940$, $p = 0.052$, $\alpha = .05$) for cross-fixation-related idle state. This suggests that the possible addition of noise related to the screen transitions did not make impossible recognition between both classes (idle and color exposure).

6 DISCUSSION AND CONCLUSIONS

In this work, we presented an assessment of the feasibility of recognizing EEG signals recorded during color exposure and idle states. We also evaluated two different types of idle states. For this assessment, we extracted two different types of features and these were classified using SVM and RF. Also, we analyzed the impact of the epochs' onset in the performance assuming a difference related to the exposure of infrequent stimuli. The obtained results provide experimental evidence that the recognition of RGB color exposure and idle states is possible (averaged accuracies higher than 75% for all cases), regardless of the kind of idle state analyzed. However, the method showed the bigger differences when we used different techniques for feature extraction than between the kind of idle states and the classifiers studied. Which suggests the pertinence of EMD-based features for this task.

It is important to highlight that when we assumed the break-related epochs as the idle state, these implied the exposure to an additional color (gray). Even though this did not seem to impact the method performance, it would be desirable a further analysis to look into if another color for idle states could have an impact on the experiment.

On the other hand, when the cross-fixation-related epochs are used as the idle states, the accuracies were lower (except for EMD-based features using SVM) than when breaks-related epochs were used. This could suggest a kind of common underlying activity going on related to attention to color exposure and cross-fixation-related epochs. Despite this common activity, the average accuracies were higher than 75% for all the classifiers and features analyzed (even removing the epochs' onset). This suggests a clear difference between this kind of idle state and color exposure too. Finally, the obtained outcomes confirm those obtained in (Torres-García et al., 2019) using a different dataset and analyzing a single type of idle state.

As future work, we will assess the methods in other related-neuro paradigms. Besides, the outcomes could be improved for an additional stage for feature selection or feature reduction such as Principal Component Analysis (PCA) and the optimization of the classifiers' hyperparameters. Also, an assessment to identify the minimum size of the epochs to distinguishing between color exposure and idle state is needed. This would be the second step towards an online color-based BCI implementation. Last, the nonstationary nature of EEG signals will make necessary the application of incremental learning in that implementation, for tuning the method's hyperparameters along the time of use of a specific subject.

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REFERENCES

AlSaleh, M., Moore, R., Christensen, H., and Arvaneh, M. (2018). Discriminating between imagined speech and non-speech tasks using eeg. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 1952–1955. IEEE.

Åsly, S., Moctezuma, L. A., Gilde, M., and Molinas, M. (2019). Towards EEG-based signals classification of RGB color-based stimuli. In *8th Graz Brain-Computer Interface Conference*, page In press.

Didiot, E., Illina, I., Fohr, D., and Mella, O. (2010). A wavelet-based parameterization for speech/music discrimination. *Computer Speech & Language*, 24(2):341–357.

Dyson, M. (2010). *Selecting optimal cognitive tasks for control of a brain computer interface*. PhD thesis, The University of Essex.

Dyson, M., Sepulveda, F., and Gan, J. Q. (2010). Localisation of cognitive tasks used in EEG-based BCIs. *Clinical Neurophysiology*, 121(9):1481–1493.

Liu, X. and Hong, K.-S. (2017). Detection of primary RGB colors projected on a screen using fNIRS. *Journal of Innovative Optical Health Sciences*, 10(03):1750006.

Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., and Yger, F. (2018). A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. *Journal of neural engineering*, 15(3):031005.

Moctezuma, L. A., Carrillo, M., Villaseñor-Pineda, L., and Torres-García, A. A. (2017). Hacia la clasificación de actividad e inactividad lingüística a partir de señales de electroencefalogramas (EEG). *Research in Computing Science*, 140:135–149.

Rasheed, S. (2011). *Recognition of primary colours in electroencephalograph signals using support vector machines*. PhD thesis, Università degli Studi di Milano.

Rasheed, S. and Marini, D. (2015). Classification of EEG signals produced by RGB colour stimuli. *Journal of Biomedical Engineering and Medical Imaging*, 2(5):56.

Åsly, S. (2019). Supervised learning for classification of EEG signals evoked by visual exposure to RGB colors. Master's thesis, Norwegian University of Science and Technology.

Soler-Guevara, A., Giraldo, E., and Molinas, M. (2019). Partial brain model for real-time classification of RGB visual stimuli: a brain mapping approach to BCI. In *8th Graz Brain-Computer Interface Conference*, page In press.

Song, Y. and Sepulveda, F. (2014). Classifying speech related vs. idle state towards onset detection in brain-computer interfaces overt, inhibited overt, and covert speech sound production vs. idle state. In *2014 IEEE Biomedical Circuits and Systems Conference (BioCAS) Proceedings*, pages 568–571. IEEE.

Torres-García, A. A., Moctezuma, L. A., Åsly, S., and Molinas, M. (2019). Discriminating between color exposure and idle state using EEG signals for BCI application. In *International Conference on e-Health and Bioengineering (EHB) 2019*, page In press. IEEE.

Torres-García, A. A. and Molinas, M. (2019). Analyzing the Recognition of Color Exposure and Imagined Color from EEG signals. In *International Conference on BioInformatics and BioEngineering (BIBE) 2019*, page In press. IEEE.

Witten, I. H., Frank, E., Hall, M. A., and Pal, C. J. (2016). *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.

Yu, J.-H. and Sim, K.-B. (2016). Classification of color imagination using Emotiv EPOC and event-related potential in electroencephalogram. *Optik*, 127(20):9711–9718.