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Specific feature selection in wearable EEG-based transducers for monitoring high cognitive load in neurosurgeons

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ABSTRACT

The electroencephalographic (EEG) features for discriminating high and low cognitive load associated with fine motor activity in neurosurgeons were identified by combining wearable transducers and Machine Learning (ML). To date, in the literature, the specific impact of fine-motor tasks on surgeons' cognitive load is poorly investigated and studies rely on the EEG features selected for cognitive load induced by other types of tasks (driving and flight contexts). In this study, the specific EEG features for detecting cognitive load associated with fine motor activity in neurosurgeons are investigated. Six neurosurgeons were EEG monitored by means of an eight-dry-channel EEG transducer during the execution of a standardized test of fine motricity assessment. The most informative EEG features of the cognitive load induced by fine motor activity were identified by exploiting the algorithm Sequential Feature Selector. In particular, five ML classifiers maximized their classification accuracy having as input the relative alpha power in Fz, O1, and O2, computed on 2-s epochs with an overlap of 50 %. These results demonstrate the feasibility of ML-supported wearable EEG solutions for monitoring persistent high cognitive load over time and alerting healthcare management.

1. Introduction

Neurosurgical practice requires to perform small and precise movements, such as suturing or manipulating small instruments, coordinating hand, wrist, and finger movements. These fine motor tasks are enabled by the use of specific cognitive resources [1]. The strong interrelations between fine motor skills and executive functions (i.e., Inhibition, Working Memory, Flexibility, etc.) has been demonstrated through neuroimaging studies and by evidence from patients with brain damage [2–4]. Moreover, neurophysiological interactions were found between the dorsolateral prefrontal cortex and the neocerebellum, i.e., the brain areas typically associated with cognition and fine motor, respectively [1,5]. Notably, cognitive tasks such as verb generation, verbal fluency, and the Wisconsin Card Sorting Test activate the dorsolateral prefrontal cortex, while also enhancing activation in the contralateral cerebellum [6–8]. In particular, in the Wisconsin Card Sorting Test, the subjects are required to categorize a set of 64 cards according to color, shape, and number by matching them to one of four stimulus cards depicting a red triangle, two green stars, three yellow crosses, and four blue circles, respectively. A feedback is given on each trial whether he or she is right or wrong. This test assesses cognitive flexibility, i.e., the ability to shift cognitive strategies in response to changing environmental contingencies [9]. The execution of fine motor activity necessitates both basic and high-order executive functions such as sustained and selective attention, planning, information processing speed, and decision-making [10,11].

Prolonged exposure to high levels of cognitive load during a task can lead to cognitive fatigue [12]. The impact of cognitive fatigue is well-documented across various professional groups. In general, a condition of cognitive fatigue led to impairments in simple and complex information processing speed and in tasks requiring executive functions over a sustained period of time [12]. Surgeons, in particular, face longer work compared to many other medical disciplines, leading to sleep deprivation and cognitive fatigue [13]. In [14], an acute mentally-fatiguing task has been demonstrated to impair fine motor skills and inhibition of irrelevant information.

Few studies in the literature investigate the cognitive load induced by fine-motor activity in surgeons. Bakhshipour et al. [15] studied the change in the concentration of oxygenated and deoxygenated

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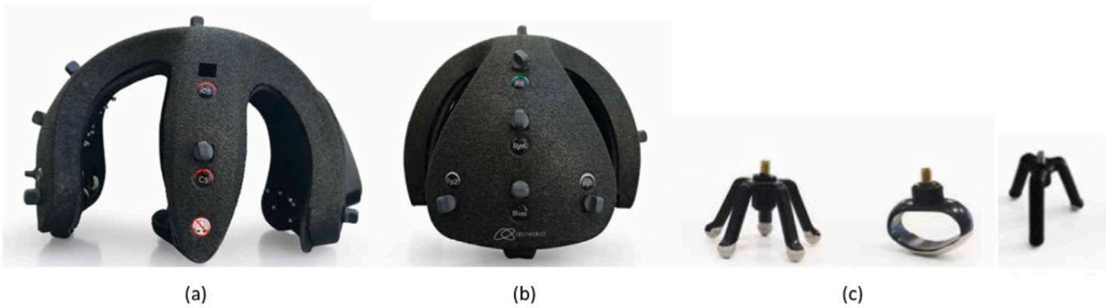

Fig. 1. The EEG cap Helmate by ab-medica: (a) side view, (b) front view, (c) electrodes [17].

hemoglobin in the prefrontal area by near-infrared spectroscopy owing to the increase in cognitive load related to fine motor skills. In [16], Authors investigated the subjective rating of mental effort and simple reaction time-based secondary task measures to predicted changes in cognitive load during the simulation of surgical activity. These studies often rely on indirect methods for monitoring brain activity, such as individual report scaling questionnaires or on brain measures with low temporal resolution and, consequently, lacking real-time information.

Recently, wearable Electroencephalography (EEG) solutions have been proposed for real-time mental monitoring of surgeons [18,19] due to EEG high temporal resolution. Most studies focusing on EEG-based monitoring of cognitive load induced by fine motor tasks rely on the EEG features selected for cognitive load induced by other types of tasks. For example, in [18], authors proposed a real-time fatigue monitoring system for laparoscopic neurosurgeons based on the computation of Mahalanobis Distance between Spectral Density Powers of pre-frontal alpha and theta. The study adopts EEG features derived from the driver fatigue detection framework, and the relationship between mental fatigue and fine motor activity was not focused on. In [20], the Authors discriminate between two classes of cognitive load induced by a laparoscopic simulation task by exploiting the frontal theta and parietal alpha bands. These features have been validated in simulated driving and flight tasks. Also in the context of robotic-assisted surgery, EEG features previously identified in driving task were employed to monitor the mental fatigue of surgeons [21].

However, the variability between tasks should be taken into account when their impact on the EEG features is explored. Generally, attempts to employ the EEG features of a particular task in detecting cognitive load during different tasks have shown poor performance [22–24]. In [25], Authors identified EEG features peculiar to the surgery context in the context of error prediction. They aim to evaluate the predictive ability of EEG data in detecting technical errors during laparoscopic surgery. However, the study did not specify the type of errors and explored the restrict set of EEG features by exploiting only statistical approaches.

In the last years, machine learning emerged as a promising approach for effective feature selection. In particular, feature selection methods can be categorized into filters and wrappers. Wrappers methods, such as Sequential Feature Selection (SFS) [26], perform better than filter methods because feature selection process is optimized for the classifier to be used [27].

Based on Machine-Learning approaches, the present study aims to select the most informative EEG features of cognitive load related to fine motor tasks with the perspective of prototyping an EEG wearable system specifically devoted to the detection of mental fatigue in surgeons.

In particular, in Section 2, the experimental sample, the hardware, the experimental protocol, and the EEG data processing are described. Moreover, in Sections 3 and 4, results are presented and discussed, respectively.

Fig. 2. Experimental protocol: participants competing two by two while performing Purdue Pegboard Test.

2. Methods and materials

2.1. Experimental sample

Six trainee neurosurgeons from different European countries (four males and two females, age 29.2 ± 1.8) were involved in the study. All participants were right-handed. They authorized inclusion in the study by signing the informed consent form. All procedures were conducted in compliance with the Helsinki declaration.

2.2. Hardware

Ab Medica Helmate (Fig. 1) is a Class IIA device used for EEG signal acquisition (certified according to the Regulation on medical devices (EU) 2017/745) [28].

The electronic is mounted on the ultralight foam structure. The transducer provides ten dry electrodes disposed according the 10/20 international system: Fp1, Fp2, Fz, Cz, C3, C4, O1, O2, AFz, and Fpz. The signals are differentially acquired with respect to the Fpz electrode and grounded to the AFz electrode. All electrodes are made of conductive rubber with an Ag/AgCl coating at their endings. Three different types of electrodes, with different shapes, are used to pass hair and reach the scalp or join to the hairless areas. The sampling rate of EEG signals is 512 Sa/s . EEG data are transmitted by Bluetooth Low Energy protocol in packets of 32 samples [29].

2.3. Experimental protocol

Participants executed the Purdue Pegboard Test (PPT) at two difficulty level while their EEG signals were acquired. The PPT is a valid and standardized test to assess fine motor skills for clinical and neuropsychological evaluation [30]. According to Spreen and Strauss [31], the PPT' score reflects a combination of different aspects of motor and cognitive speed, coordination and effort. An increasing cognitive load is required to the subject by changing the level of difficulty of the test [32]. Therefore, the PPT could allow to investigate the increasing cognitive load linked to fine-motor activity.

Participants underwent the Purdue Pegboard Test (PPT) in two distinct modes: (i) *right hand* and (iv) *assembly*. Specifically, subjects were asked to first perform the task three times in the *right hand* mode

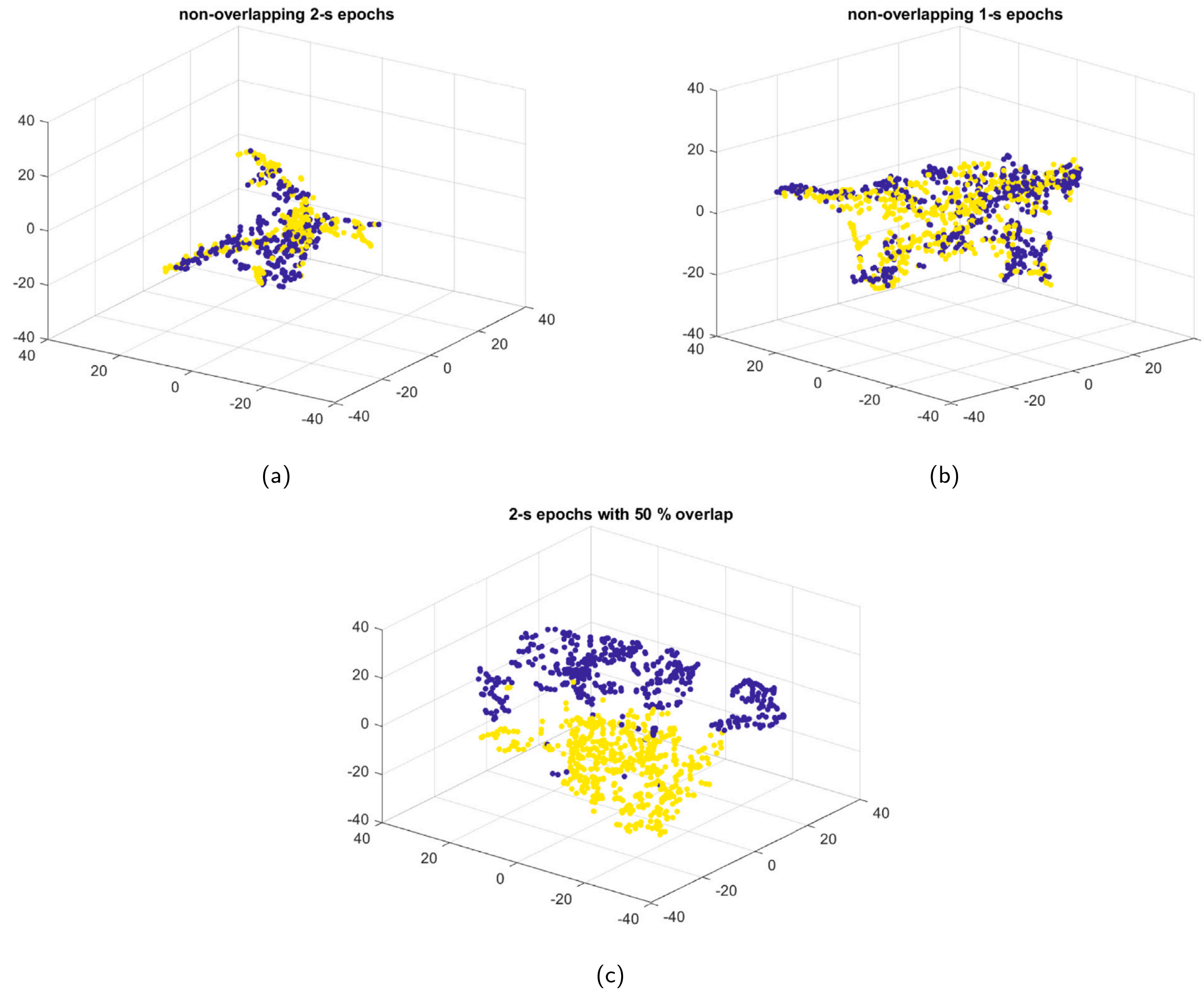

Fig. 3. Impact of epoch length and overlap on data separability. Labeled data for (a) non-overlapping 2-s epoch, (b) non-overlapping 1-s epoch, and (c) 2-s epoch with 50% overlap. EEG features of low (in blu) and high (in yellow) cognitive load.

and then three times in the *assembly* mode. The task was organized as a competitive challenge, with participants competing two by two, as illustrated in Fig. 2.

The primary objective of the task was to insert as many pins as possible into a board featuring two perpendicular lines, each containing 25 evenly spaced holes, within 30 s. Specifically, in the *right hand* modality, participants were instructed to pick up and insert pins using their right hand into the right line of holes on the board. In the *assembly* modality, participants were tasked with inserting a pre-defined structure, consisting of a pin, a washer, a bearing, and a second washer, into the designated hole by using both hands. Participants had a fixed time limit of 30 s for pin insertion.

A pause of 30 s was set between the trials. The synchronization between each test and the EEG acquisition was ensured by a countdown scanned by a software interface. At the end of the countdown, the participant starts the execution of the task and the experimenter places a marker on the EEG signal from the keyboard. The EEG device was held on the participant's head for the duration of the experiment in order to limit the sources of uncertainty related to the positioning of the electrodes and the pressure exerted by the electrode on the skin. Each PPT mode was associated with a specific cognitive load condition label: *right hand* was designated as *low cognitive load*, while *assembly* modality as *high cognitive load*.

2.4. EEG data processing

A Wilxocon test [33] was carried out on the mean and the standard deviation of the acquired EEG trials in order to evaluate the quality of the data. The analysis revealed that the EEG trials of all task condition, namely, *right hand* (47.04 ± 49.19 μV) and *assembly* execution modality (49.84 ± 50.92 μV), were comparable as far as the mean (p-value = 0.580) and standard deviation values (p-value = 0.370) are concerned.

In the artifact removal phase, EEG data were filtered by means of the fourth-order Butterworth bandpass filter [0.5–45] Hz. Then, the *Artifact Subspace Reconstruction* (ASR) [34] with a cutoff of 15 was applied in order to remove the transient artifacts from the signal. The ASR is a component-based artifact removal method and works by decomposing the signal into components and by removing components whose amplitude exceeds a certain threshold (automatically calculated depending on the variance of the signal). Finally, the signal is reconstructed by considering the remaining components.

The EEG features extraction was inspired by the literature reported in the Introduction. Therefore, the absolute (abs) and relative (rel) powers were computed in the delta ([1–4] Hz), alpha ([8–13] Hz), theta ([4–8] Hz), beta ([13–30] Hz), low beta ([13–20] Hz), high beta ([20–30] Hz), and gamma ([30–45] Hz) bands for three different epochs length: (i) non-overlapping 1-s epochs, (ii) non-overlapping 2-s epochs,

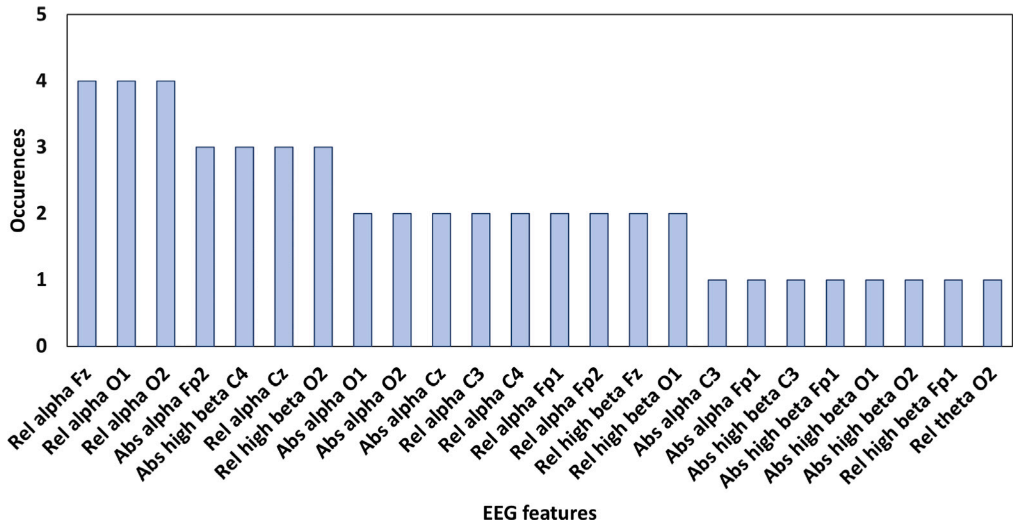

Fig. 4. Histogram of the occurrences of the ten features that individually achieve the highest accuracy for each classifier.

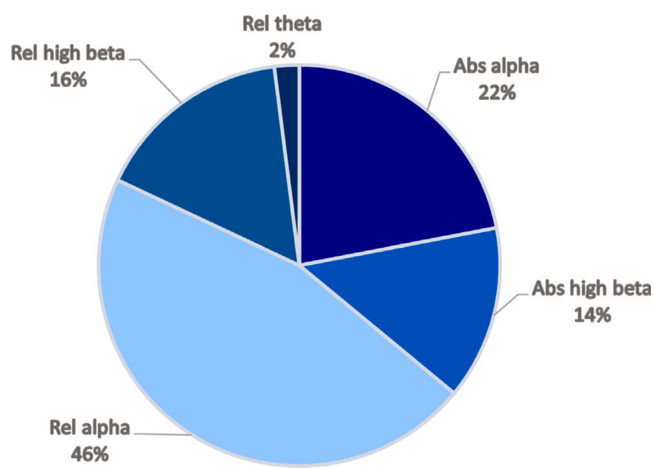

Fig. 5. Pie chart of the band information of the features that individually achieve the highest accuracy for each classifier.

and (iii) 2-s epochs with 50% overlap. The graphs (Fig. 3) based on the t-distributed Stochastic Neighbor Embedding (t-SNE) show in a bi-dimensional space the EEG features at varying the epoch-length and the overlap condition. Choosing an increase in the analysis window and a 50% overlap improves the separability of the data between classes and simplifies the classification problem. This makes the classification process simpler, requiring fewer features, and allows the task to be tackled with a classifier with a low number of identifiable parameters, even from datasets that are not necessarily large.

In the feature selection phase, the Sequential Feature Selection (SFS) algorithm [35] was employed. The SFS is a machine learning algorithm to select the most informative subset of EEG features by progressively adding (*forward*) or removing features from the overall features (*backward*). The features subset selection adopts the criterion of maximizing the cross-validation score of an estimator. In this study, the SFS was implemented in the *forward* modality and the considered estimators were: k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Linear Discriminant Analysis (LDA). A Leave-One-Subject-Out (LOSO) cross-validation technique was used. The LOSO approach was adopted to evaluate the generalization capabilities of the classifier [36] by assessing the accuracy of tests on data belonging to a subject never seen before. In particular, all classifiers were subjected to the same SFS process. In the first round, each classifier was trained and tested on the same features, using only one at a time. At each subsequent step, as required by the SFS algorithm, the combination of features (namely, the *robust features*) that maximizes accuracy for each classifier was identified. With the adoption of the Leave-One-Subject-Out approach, one-sixth of the epochs were used for testing and the remainder as training. The number of features to be selected was varied until the best performance was obtained.

3. Results

The accuracy and the subset of EEG features achieving the best performance at varying the SFS estimator and the epoch length are reported in Table 1.

Further analysis was conducted for the condition (i.e., epoch length and classifier) achieving the best accuracy. In particular, the accuracy achieved from each feature singularly was computed. The EEG features are sorted decreasingly for each classifier according to the accuracy achieved. Then, the top ten features that singularly achieve higher accuracy have been focused on (Table 2). The band information of the selected EEG features is shown in the pie chart in Fig. 5. In particular, the EEG bands achieving higher accuracy are alpha (68%) and high beta (30%). The histogram of the occurrences for the top ten significative EEG features of each classifiers is reported in Fig. 4.

4. Discussion

This study aims to identify the most informative EEG features from signal acquired by wearable transducer (wireless, low number of channels, dry electrodes) for detecting cognitive load associated with fine motor activity in neurosurgeons. Most of the existing contributions on EEG-based monitoring of cognitive load induced by fine motor tasks are based on the EEG features of cognitive load validated for other tasks. In particular, the mostly employed EEG features in detecting surgeons' cognitive load, namely the alpha and theta power in frontal regions, are proposed due to their effectiveness in the context of car driving or air flight. As a consequence, the impact on cognitive load of fine motor activity peculiar to surgical practice might be overlooked when using nonspecific EEG features.

In order to assess the impact of fine motor engagement on the electroencephalographic signal, a gold standard experiment for selective activation of fine motor activity was proposed. In addition, a feature selection procedure among the 112 features in input (8 channels $\times$ 7 bands $\times$ 2 kinds of computation) was performed by applying a machine

Table 1
Percentage accuracy (mean and standard deviation) obtained by the subset of EEG features selected by the SFS in combination with different classifiers and epoch length. Higher values are in bold.

Epoch length	Classifier	Number of EEG features	EEG features	Accuracy (%)
1 s - no overlap	kNN	14	Abs gamma at Fz Rel delta at O1 Rel theta at Fz and C4 Rel low beta at C3, Cz, and C4 Rel high beta at Fp1, Cz, Fz, and O2 Rel gamma at C3, Fp1, and Fz	66.4 ± 3.0
	SVM	3	Abs theta at C3 Abs low beta at C3 and Fz	67.3 ± 8.9
	LDA	17	Abs. delta at Fp2 and C4 Abs. theta at Fp1 and Cz Abs. alpha at Fz Abs. low beta at Cz Abs. high beta at Cz and Fz Abs. gamma at Fz Rel. theta at Fz and C4 Rel. alpha at Fp1 Rel. low beta at Cz and Fp2 Rel. high beta at O1 and Cz Rel. gamma at Cz	74.2 ± 7.2
	ANN	5	Abs theta at C3 Rel delta at O1 Rel theta at Fz Rel low beta at Cz Rel high beta at C3	70.2 ± 10.2
	RF	9	Abs theta at Fz Abs high beta at Fp2 Abs gamma at Fz Rel delta at O1 Rel delta at Fz Rel alpha at O1, C3, and Fz Rel high beta at C4	73.5 ± 8.4
2 s - no overlap	kNN	8	Abs. theta at C3 Abs. high beta at Cz Rel. theta at Fp2 Rel. high beta at O1 Rel. gamma at C3, Cz, Fp2 and O2	57.8 ± 15.7
	SVM	7	Abs. theta at C3 Abs. low beta at C3, Fp1, Cz and Fz Rel. delta at O1 Rel. gamma at O2	60.9 ± 16.1
	LDA	5	Rel. delta at O1 Rel. theta at Cz, Fz, and C4 Rel. gamma at O2	62.2 ± 9.2
	ANN	1	Abs theta at Cz	70.2 ± 21.9
	RF	5	Abs theta at C4 Rel theta at Fz and C4 Rel low beta at C4 Rel gamma at O1	64.8 ± 4.7
2 s - 1 s overlap	kNN	1	Rel. alpha at O2	**99.9 ± 0.2**
	SVM	2	Rel. high beta at O2 Rel alpha at Fz	**100.0 ± 0.0**
	LDA	7	Abs. delta at Fp1 and O1 Rel. delta at Cz Rel. theta at Fp2 Rel. alpha at Fz Rel. low beta at C4 Rel. high beta at O1	**99.7 ± 0.3**
	ANN	1	Abs delta at C3 Abs alpha at O1 and Fp2	**100.0 ± 0.0**
	RF	1	Rel alpha at O2	**100.0 ± 0.0**

learning algorithm. In particular, two different analyses were carried out. In the first analysis, the SFS was used to select the subset of EEG features achieving the highest accuracy at varying the SFS estimator and the epoch length. The pre-processing leading to higher average accuracy in the previous stage is also used in the subsequent analysis. The second analysis consists of (i) sorting the 112 features decreasingly for each classifier according to the accuracy achieved by each feature individually, (ii) making a histogram of the occurrences for the top ten features of each classifier. The aim of these analyses was the identification of the most robust EEG features as they maximize accuracy regardless of classifier, namely the features that are most likely to be effective identifiers of the cognitive phenomena being investigated.

The first analysis showed that the best performance (accuracy of $100.0 \pm 0.0\%$) was achieved with 2-s epochs and overlap of 1 s by SVM, ANN and RF. In general, accuracy above 99.0% were achieved by all classifiers for 2-s epochs with 1 s overlap. Compared with the 1 s window, the 2-s observation guarantees higher frequency resolution and a better normal mode noise rejection due to the signal integration within a wider temporal window. Moreover, the introduction of the overlap while ensuring for each time window an appropriate duration, allows providing the classifiers with a more conspicuous training dataset. In particular, already in this first analysis, the relevance of the alpha-band relative power feature in O2 emerges, allowing the achievement of accuracies above 99.0% with KNN and RF classifiers when used as the only input.

The second analysis revealed that the 68% and 30% of the 50 (10 features × 5 classifiers) EEG features achieving higher accuracy belong to alpha and high beta band, respectively. In the histogram of occurrences, channel information revealed that the most discriminating EEG features are relative to the occipital and fronto-parietal regions. Relative alpha power in Fz, relative alpha power in O1 and O2 showed the highest number of occurrences. In particular, decrease in relative alpha at O1 (*p-value* = 0.031) and O2 (*p-value* = 0.031) and in relative alpha at Fz (*p-value* = 0.031).

These results are partially in agreement with previous studies. In fact, alpha and theta rhythms in the pre-frontal cortex were recognized as the EEG features more informative with respect to the cognitive load related to surgical activity by Zander et al. [20]. However, Zander et al. observed a decreased occipital alpha activity during performance of technically challenging tasks. The difference in the feature trend could reflect the different experimental condition between the two difficulty levels of the task proposed by Zander et al. and the impact on the visual cortex. Indeed, from the visual stimulation related to the manipulation of real objects (simpler task) participants are required to realize an on-screen virtual experience (more difficult task). In the literature, alpha power over the contralateral central area was observed better discriminating between left and right hand movement imagination [37]. Therefore, the high accuracy observed in alpha band could be related to unilateral versus bilateral movement tasks instead of low versus high cognitive tasks. This strengthens the hypothesis that the relative alpha power in O1 and O2 could be effective identifiers of cognitive load related to fine motor activity.

In addition, the relative alpha power in O1 and O2 were considered in the literature in the context of cognitive fatigue resulting from prolonged time spent on a task (TOT). In particular, in [38], a significant increase of the PSD in the alpha and theta bands was documented in the occipital, medial and frontal regions during fatigue over a long period. However, in the present study, a decrease in relative alpha in O1 and O2 was observed. This discrepancy could be due to the different mental conditions analyzed. In particular, in [38], the onset of a fatigue condition is considered. While, in the present study, a condition of increased cognitive load is taken into account. It is reasonable to assume that the two conditions can be characterized by opposite trends of the feature under consideration: a decrease in relative alpha characterizes an increase in cognitive load, whereas, when fatigue arises, the value of the feature increases. Therefore, occipital relative alpha power emerges as promising candidate (to be further investigated in future studies considering a larger experimental sample) for the investigation of impact of fine motor activity on the cognitive load.

However, despite these observations, the reported accuracies across the analyzed features and regions appear to be largely consistent. This suggests that while certain EEG features and brain regions may show promise in discriminating cognitive load, the overall impact on accuracy remains uniform across the analyzed features and regions. Consequently, the implications of these findings on the discriminative power of EEG features should be interpreted with caution, considering the uniformity in accuracy values across different features and regions.

Table 2
Top ten EEG features achieving the highest accuracy (mean and standard deviation) for each classifier in ascending order. The considered epoch length of the EEG features is 2 s with 50% of overlap.

Classifier	EEG features	Accuracy (%)
KNN	Rel alpha O2	99.9 ± 0.1
	Abs alpha Fp2	99.8 ± 0.2
	Abs alpha O2	99.8 ± 0.2
	Abs high beta C4	99.8 ± 0.2
	Rel alpha O1	99.8 ± 0.2
	Rel alpha Fp1	99.8 ± 0.2
	Rel alpha Cz	99.8 ± 0.2
	Rel alpha Fz	99.8 ± 0.2
	Rel alpha Fp2	99.8 ± 0.2
	Rel high beta O2	99.8 ± 0.2
SVM	Rel high beta O2	99.7 ± 0.3
	Rel alpha O1	99.3 ± 0.4
	Rel alpha O2	99.3 ± 0.7
	Rel high beta O1	99.3 ± 0.7
	Rel alpha Fz	99.2 ± 0.5
	Rel alpha Cz	99.1 ± 0.4
	Rel alpha C4	98.9 ± 0.9
	Rel high beta Fz	98.9 ± 0.3
	Rel theta O2	98.8 ± 0.8
	Rel alpha C3	98.8 ± 1.6
LDA	Rel high beta O1	88.8 ± 0.7
	Rel high beta O2	88.0 ± 2.9
	Rel alpha O2	87.5 ± 4.2
	Rel alpha Fz	86.7 ± 2.9
	Rel alpha C4	86.6 ± 3.0
	Rel alpha Cz	86.3 ± 3.2
	Rel alpha O1	86.1 ± 2.2
	Rel alpha C3	86.1 ± 2.2
	Rel high beta Fp1	85.9 ± 2.7
	Rel high beta Fz	85.9 ± 2.6
ANN	Abs high beta O1	98.9 ± 1.0
	Abs high beta O2	98.9 ± 0.9
	Abs alpha O1	98.6 ± 1.4
	Abs high beta C4	96.7 ± 3.3
	Abs alpha C3	96.0 ± 4.0
	Abs high beta Fp1	96.0 ± 1.9
	Abs alpha Cz	95.9 ± 4.0
	Abs alpha Fp2	95.8 ± 3.2
	Abs high beta C3	95.8 ± 3.8
	Abs alpha Fp1	95.1 ± 4.0
RF	Rel alpha O2	99.9 ± 0.1
	Abs alpha Fp2	99.8 ± 0.2
	Abs alpha O2	99.8 ± 0.2
	Abs high beta C4	99.8 ± 0.2
	Rel alpha O1	99.8 ± 0.2
	Rel alpha Fp1	99.8 ± 0.2
	Rel alpha Fz	99.8 ± 0.2
	Rel alpha Fp2	99.8 ± 0.2
	Abs alpha Cz	99.7 ± 0.2
	Abs alpha O1	99.7 ± 0.3

Note: In each cell of the "Accuracy (%)" column, the mean accuracy is followed by the standard deviation.

5. Conclusions

In this study, the electroencephalographic (EEG) features for detecting cognitive load associated with fine motor activity in neurosurgeons were investigated from signal acquired by wearable transducer (wireless, low number of channels, dry electrodes). The EEG signal of six neurosurgeons was monitoring by using an eighth-channel EEG transducer during the execution of a standardized test of fine motricity assessment (PPT). In particular, participants were asked to perform the PPT at two level of difficulty. Each PPT mode was associated with a specific cognitive load condition label: right hand was designated as low cognitive load, while assembly modality as high cognitive load. The absolute and relative powers were computed in the delta, alpha, theta, beta, low beta, high beta, and gamma bands for three different epochs length: (i) non-overlapping 1-s epochs, (ii) non-overlapping 2-s epochs, and (iii) 2-s epochs with 50% overlap. The Sequential Feature Selection algorithm embedding five ML estimator was employed to find the most informative subset of EEG features to discriminate between the two cognitive load conditions elicited by fine motor tasks. The 100% of accuracy was achieved by the Random Forest using the alpha-band relative power in O2, computed on 2-s epochs with 50% overlap. Moreover, the EEG features singularly achieving the higher accuracy with all the considered classifiers were: relative alpha power in Fz, O1 and O2. In particular, relative alpha power in O1 and O2 emerge as relevant features for the characterization of the impact of motor activity on cognitive activity, while the high accuracy observed in alpha band in the central region might be related to unilateral versus bilateral movement tasks instead of low versus high cognitive tasks. However, the implications of these findings on the discriminative power of EEG features should be interpreted with caution, considering the uniformity in accuracy values across different features and regions.

In future works, randomized experimental protocol will be implemented in order to minimize the confounders' (time on task and task learning) impact and new EEG features (entropy, coherence etc.) will be explored.

CRediT authorship contribution statement

Pasquale Arpaia: Writing – review & editing, Supervision. **Mirco Frosolone:** Writing – original draft, Data curation. **Ludovica Gargiulo:** Writing – original draft, Data curation. **Nicola Moccaldi:** Writing – original draft, Supervision, Conceptualization. **Marco Nalin:** Conceptualization. **Alessandro Perin:** Conceptualization. **Cosimo Puttilli:** Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pasquale Arpaia reports financial support was provided by The Ministry of Enterprises and Made in Italy. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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