Mental Effort Detection When Using a Motor Imagery-Based Brain-Computer Interface

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Pasquale Arpaia[1,2,3], Antonio Esposito[1,2], Ludovica Gargiulo[1,2], Nicola Moccaldi[2,4], Angela Natalizio[2,5], Marco Parvis[5], and Rachele Robbio[1]

***Abstract*—A wearable electroencephalographic (EEG) device-based method for the classification of the mental effort during motor imagery is presented. The solution can be used to improve the training of novice surgeons involved in minimally invasive surgery. The method was validated on a public dataset comprising recordings from two participant groups: the control group (engaging in pure motor imagery tasks without feedback) and the neurofeedback group (receiving feedback during their mental tasks). In particular, a previous work on the same dataset found a higher cognitive effort for the neurofeedback group than for the control group, which was confirmed by the results of the NASA-TLX questionnaire. EEG signals were acquired with an 8-electrode dry device. The EEG features of the mental effort were identified by using the Sequential Feature Selector (SFS), in combination with different classifiers, on the EEG data of the control group. In order to classify between low and high mental effort (baseline accuracy of 50 %), four EEG features and the Multi-Layer Perceptron classifier resulted in the best combination for the mental effort assessment in the control group, achieving an average accuracy of 82.1 ± 8.7 %. The 4 features identified were: (i) theta-to-alpha ratio on Fz channel, (ii) beta-to-delta ratio on O1 channel, (iii) theta-to-beta ratio on FP1 channel, and (iv) (theta+alpha)/beta on FP1 channel. The same pipeline was employed on the neurofeedback group, achieving an average accuracy of 84.0 ± 6.8 %. These findings are in accordance with the results of NASA-TLX questionnaire. This work demonstrated the feasibility of assessing cognitive effort in real-time by means of wearable EEG device during motor imagery tasks. Thus, neurofeedback-supported motor imagery systems can be enriched by a new module to adapt the training to the novice surgeons and optimise learning outcomes.**

***Index Terms*—Electroencephalography; mental effort; brain-computer interfaces; motor imagery.**

I. Introduction

In the field of surgery, fine motor control is crucial for successful outcomes. Surgeons often need to perform delicate and precise movements, such as suturing or manipulating small instruments, during surgical procedures. These movements require a high level of dexterity and coordination, which can be improved through practice [1]. However, there is a lack of preparation of graduate trainees due to few clinical opportunities to practise these skills [2]. A method that could be effective for enhancing motor control in surgeons is the use of motor imagery tasks [3].

Motor imagery is the mental execution of specific movements without physically executing them [4]. Mental training through motor imagery was found useful in many fields, including sport, music and rehabilitation medicine [5]. Motor imagery has been proved to be effective in improving technical skills of novice surgeons in minimally invasive surgery [5]. Experienced surgeons have been found to display higher motor imagery ability for robotic surgery, indicating that motor imagery is a component of surgical expertise [3].

Subjective questionnaires have traditionally been used to assess motor imagery ability [6], [7]. However, they have limitations in terms of reliability and objectivity. To overcome these limitations, assessments of motor imagery ability based on electroencephalography (EEG), a non-invasive technique that measures the electrical activity of the brain, are used. By examining changes in EEG signals during motor imagery tasks, objective information on an individual's motor imagery capacity can be obtained [8]. The EEG signal was found to be sensitive in assessing the motor imagery skills of the robotic suture, showing differences between beginners, intermediates and experts [3]. In particular, the alpha-band power in frontal and parietal regions of novices and intermediates was almost 10 times lower than that of experienced surgeons. However, EEG-based neurofeedback should be investigated to enhance training.

In the context of brain-computer interfaces (BCIs), EEG-based motor imagery assessments offer not only an objective measure of the user's imaginative abilities, but can also provide the user with a feedback [9]. Neurofeedback, i.e. real-time feedback on brain activity, allows users to adapt and refine motor imagery processes within a BCI framework, promoting greater engagement and continuity in the motor imagery task [10]. It may offer a mechanism to influence and accelerate the learning process, enhancing surgeon training [3].

However, prolonged motor imagery can induce mental fatigue, reducing its positive effects [11], [12]. To maximise the training of surgeons, another advantage of BCIs can be exploited, namely the monitoring of the user's cognitive state. By monitoring the user's cognitive state during motor imagery, it is possible to assess the level of mental effort exerted by the subject [13]. This information is crucial because it can provide valuable insights into the effectiveness of motor imagery training and allow for customised interventions to

[1]Department of Electrical Engineering and Information Technology (DIETI), Università degli Studi di Napoli Federico II, Naples, Italy
[2] Università degli Studi di Napoli Federico II - Augmented Reality for Health Monitoring Laboratory (ARHeMLab), Naples, Italy
[3] Centro Interdipartimentale di Ricerca in Management Sanitario e Innovazione in Sanità (CIRMIS), Università degli Studi di Napoli Federico II, Naples, Italy
[4] Department of Engineering for Innovation, University of Salento, Lecce, Italy
[5]Department of Electronics and Telecommunications (DET), Politecnico di Torino, Turin, Italy

optimise learning outcomes.

This study is based on a public dataset in which two groups of subjects used a BCI based on motor imagery for five consecutive sessions [10]. The subjects were divided into a control group, which never received feedback as a result of the motor task, and a neurofeedback group, which received multimodal feedback. The EEG signal was acquired by means of a device with only eight dry electrodes, promoting wearability and user comfort.

The goal of this study is to demonstrate the feasibility of a wearable electroencephalographic (EEG) device-based method for the classification of the mental effort during motor imagery.

The device is a candidate as a tool for adaptive technology-based training [14] of surgeons since it is based on innovative neural interfaces and can potentially adapt to the engagement condition detected in the subject through the EEG signal.

The remainder of the paper is organized as follows: Section II recalls the inherent literature, Section III describes the dataset, and explains data reorganization and processing, while Section IV reports the results of the study.

II. Background

Several studies in the literature focused on the identification of mental effort on an electroencephalographic basis. In [15], 25 students were asked to solve 24 scientific problems of two complexity levels. The EEG signal was acquired during task execution to assess changes in the theta and alpha band. The study highlights how increasing mental effort results into a synchronization of theta waves and a desynchronization of alpha waves. Specifically, the theta in the frontal and occipital regions are significantly higher than those in the central and parietal regions.

In [16], the mental effort is associated with gross and fine motor exercises mediated by a robot. The EEG was acquired from FP1, F3, FC3, C3, C4, P3, O1, and T7. During fine motor exercises, an increase of powers for theta relative and alpha relative resulted in all the channels. In contrast, a general decrease for delta relative power was found, particularly in the FP1 channel.

The Tetris game with three difficulty levels was used in the study presented in [17]. Auditory probes were used to assess attention span while participants played the game. The theta/alpha ratio power revealed that it was generally significantly higher for the medium and hard challenge levels compared to the easy challenge level.

In [18], participants performed a two levels cognitive task while either seated or walking on a dual-belt treadmill. The cognitive task required participants to detect stimuli that took the form of objects composed of various shapes and colors. Statistical analysis revealed significantly higher frontal theta/alpha power when the more difficult task was performed. Furthermore, the same feature was sensitive for the walking condition compared to the seated one.

In [19], EEG features were input into different classifiers, namely Logistic Regression, Support Vector Machine and Decision Tree. The most discriminant feature between resting state and the execution of multitasking SIMKAP test resulted the alpha-to-beta ratio power from parietal and frontal areas.

The study presented in [20] performed an EEG-based classification of mental states related to (i) resting, (ii) mental reading and (iii) mental calculations. The results of this study suggest that cognition index which is a combination of EEG band ratios based on theta, alpha, beta, and gamma bands was an excellent predictor for detecting cognitive states. The subject-independent optimal features also included theta to gamma ratio, alpha to beta ratio, Hjorth mobility and entropy over the optimal channels mainly located in parietal, parieto-occipital, frontal, and occipital regions. These features combined with coherence and phase-locking value (PLV) between distinct brain regions provided the highest recognition accuracy for cognitive states.

III. Materials and methods

The goal of this study is to demonstrate the feasibility of a method based on EEG signal acquired with an 8 dry electrode device to assess the mental effort of novice surgeons supported by neurofeedback during motor imagery tasks. The starting point of the proposed method concerns the results of the NASA-TLX questionnaire, administered to the participants, which indicated that the neurofeedback group perceived greater mental effort. Accordingly, a proper strategy to separate the impact on mental effort of (i) the succession of mental tasks execution and (ii) the neurofeedback was adopted. In particular, the most significant EEG features for mental effort detection were identified on the control group as task execution time increased. Then, the same features were validated for the detection of mental effort on the neurofeedback group.

A. Dataset

A public dataset was exploited in this study [10]. It comprises the EEG data of 27 healthy subjects who participated in a BCI study based on motor imagery. Participants were divided into two groups: a control group (13 subjects) that received no feedback and a neurofeedback group (14 subjects) that received multimodal feedback during sessions in response to the motor imagery task. Each participant completed five one-hour sessions. They imagined left and right hand movements according to a synchronous paradigm. Each session comprised six runs each with 30 randomised trials (15 per task) for a total of 180 trials per session. The control group performed the six runs without ever receiving feedback. For the neurofeedback group, the first three runs were without feedback and were used to calibrate the system; the last three runs provided multimodal feedback to the participants. EEG signals were acquired via eight dry electrodes with a sampling rate of 512 Hz. Electrode placements followed the international 10-20 EEG system, with channels located at FP1, FP2, Fz, Cz, C3, C4, O1, and O2, while reference and bias electrodes were placed in the frontal region at AFz and FPz, respectively. For the complete data set and experimental details, please refer to https://metroxraine.org/metroxraine2022/contest-dataset.

At the end of the motor imagery sessions, participants from both groups were administered the NASA-TLX questionnaire [21]. Upon analyzing the questionnaire results, the neurofeedback group reported a perceived higher level of effort compared to the control group. This discrepancy was statistically significant, as expected due to the additional engagement required for the neurofeedback component.

B. Data reorganization

Participants performed six motor imagery runs in two experimental phases, each of three runs. The runs lasted 4 minutes and were all interspersed with short breaks. Subjects assigned to the control group performed both phases without neurofeedback, while subjects assigned to the neurofeedback group were supported by neurofeedback during phase 2.

In this study, data were re-labeled to detect mental effort rather than motor imagery. To achieve this, the first and sixth runs of the first session were used to represent low and high mental effort, respectively. The assumption of increased effort as time passes requires participant's performance being constant during the whole session. This assumption was statistically verified by comparing the classification accuracy of motor imagery tasks between phase 1 and phase 2 of all sessions in general for the participant belonging to the control group. The Wilcoxon test ($\alpha = 0.05$) was carried out to assess the average difference in the control group subjects performances between phase 1 and phase 2. Since the EEG features for the detection of mental effort were identified on the control group, the statistical analysis was performed on this group. No difference in the mean between the two performance distributions was assumed as the null hypothesis.

C. Signal preprocessing and Feature extraction

A 4^{th} order Butterworth bandpass filter with cutoff frequencies between $1\,\text{Hz}$ and $45\,\text{Hz}$ was applied to the raw EEG data to extract the frequency bands of interest. Subsequently, artifacts were removed from the EEG signal using the Artifact Subspace Reconstruction (ASR) setting a cutoff for rejection of 11.75 (this rejection threshold parameter value was found to be the best in the case of 8 channels in the study [22]). Next, the signals were segmented into $1.5\,\text{s}$ epochs. Fast Fourier Transform (FFT) was applied to segmented signals to calculate absolute powers in the *delta* $[1-4]$ Hz, *theta* $[4-8]$ Hz, *alpha* $[8-13]$ Hz, *beta* $[13-30]$ Hz, *low-beta* $[13-20]$ Hz, *high-beta* $[20-30]$ Hz, *gamma* $[30-45]$ Hz, frequency bands. Starting from the absolute powers, the EEG features related to cognitive effort ([16]–[20]) were calculated:

- *theta-to-beta ratio*
- *theta-to-alpha ratio*
- *beta-to-delta ratio*
- *(beta+gamma)/delta*
- *(theta+alpha)/beta*

It is worth noting that the last feature corresponds to the inverse of the engagement index [23]. Feature extraction was performed the same way on both groups, while feature selection was performed only on the control group and is explained in the next subsection.

D. Feature selection and classification

In the feature selection phase, the EEG features for the detection of mental effort were identified by considering the first and the last run of the control group. Then, the previously selected EEG features were employed for assessing the level of mental effort on the neurofeedback group. Feature selection was performed on the 13 subjects belonging to the control group, considering the first run (low mental effort) and the last run (high mental effort) of the first session. An algorithm belonging to the wrapped methods [24], namely the Sequential Feature Selection (SFS) algorithm, was used. The SFS adds or removes features from the dataset iteratively based on the cross-validation score of an estimator. For this study, Forward-SFS, based on the addition of features, was implemented and Leave-One-Subject-Out (LOSO) cross-validation technique was used. The employed estimators were: k-Nearest Neighbor (kNN), Random Forest (RF), Gaussian Naive-Bayes (NB), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). 40 features were provided as input to the SFS, i.e. the 5 features previously extracted for all 8 channels.

The number of features to be selected was varied until the best performance was obtained. Next, starting from the best classifier and the features obtained in the previous phase, a two-level classification of mental effort was conducted on 13 subjects belonging to the neurofeedback group considering the first run (without neurofeedback) and the last run (with neurofeedback) of the first session. In this phase, the subject 7 of the neurofeedback group, with very low performances, was discarded to allow a balance of samples between the two groups. A LOSO cross-validation was employed in an inter-subject setting.

IV. Results

The Wilcoxon test on the the classification accuracy of motor imagery tasks revealed a p-value of 0.845. Consequently, the null hypothesis was not rejected and the compatibility between the performances of phase 1 and phase 2 was accepted. Therefore, a constant application during the whole session was assumed. The box-plots relating to the two phases accuracies of the control group are shown in Fig. 1. The comparability between the accuracy values of the two conditions demonstrates perseverance in application during the task. This result reasonably suggests that the participants expended more mental effort during the last run of the session.

Average classification accuracy of the mental effort level considering the control group for the various classifiers, as the number of features to be selected provided to the SFS increases, is shown in Tab. I. In all cases, maximum performance is achieved with 4 features. In particular, the highest performance (average accuracy of $82.1\ \% \pm 8.7\ \%$) was obtained when the SFS algorithm in combination with the MLP classifier selected the following features: (i) theta-alpha ratio on Fz channel, (ii) beta-delta ratio on O1 channel, (iii)

TABLE I
PERCENTAGE CLASSIFICATION ACCURACY (MEAN AND STANDARD DEVIATION) OF THE MENTAL EFFORT DETECTION IN THE CONTROL GROUP, AT VARYING THE NUMBER OF THE FEATURES AND THE CLASSIFIER ADOPTED WITHIN THE SFS ALGORITHM.

Number of selected features	**Classifier**				
	MLP	**kNN**	**NB**	**RF**	**SVM**
1	60.8 ± 14.1 %	56.5 ± 11.1 %	54.9 ± 10.9 %	60.4 ± 15.1 %	62.3 ± 16.6 %
2	62.4 ± 14.6 %	61.1 ± 10.1 %	57.0 ± 9.7 %	64.9 ± 9.6 %	65.3 ± 13.7 %
3	64.0 ± 12.8 %	72.2 ± 10.3 %	57.2 ± 10.5 %	69.7 ± 8.5 %	71.3 ± 9.6 %
4	**82.1±8.7 %**	77.9 ± 6.9 %	57.2 ± 10.5 %	70.6 ± 9.6 %	81.6 ± 5.9 %

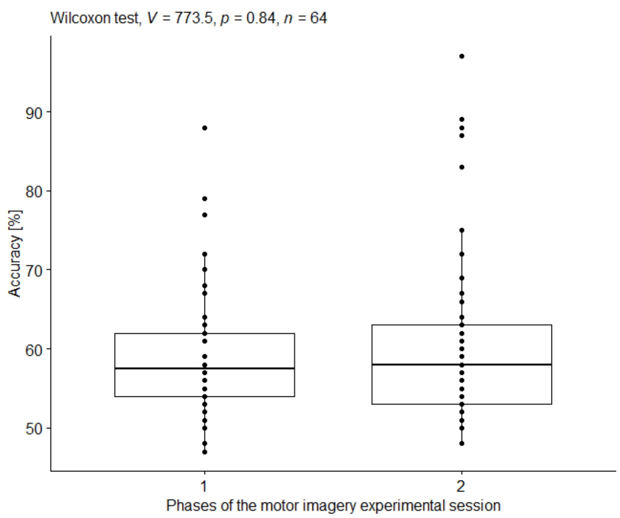

Fig. 1. Box plots: percentage classification accuracy for the participants from control group when the motor imagery tasks were performed in phase 1 and phase 2 of the session, respectively.

theta-beta ratio on FP1 channel, and (iv) (theta+alpha)/beta on FP1 channel.

TABLE II
PERCENTAGE CLASSIFICATION ACCURACIES (MEAN AND STANDARD DEVIATION) OF MPL IN DISCRIMINATING MENTAL EFFORT ON THE NEUROFEEDBACK GROUP AT INCREASING THE NUMBER OF INPUT FEATURES. FEATURE WERE SELECTED ACCORDING TO THEIR IMPACT ON CLASSIFICATION ACCURACY OF THE CONTROL GROUP, IN DECREASING ORDER.

Features	**Channel**	**Accuracy**
Theta-Alpha ratio	Fz	50.6 ± 7.6 %
& Beta-Delta ratio	O1	51.1 ± 13.5 %
& Theta-Beta ratio	FP1	50.8 ± 15.6 %
& (Theta+Alpha)/Beta	FP1	**84.0±6.8 %**

In Tab. II, average accuracies for the MLP classifier of mental effort in neurofeedbak group are shown. The best average accuracy (84.0 % ± 6.8 %) was achieved with the 4 previously selected features. The higher mean accuracy with respect to control group (although the ranges of standard deviations are slightly overlapping) are in accordance with the NASA-TLX results. Therefore, the hypothesis that mental effort is promoted by neurofeedback appears compatible with the experimental results.

V. DISCUSSION

Motor imagery-based Brain-Computer Interfaces (BCIs) can have different fields of application, including enhancing surgeons' surgical skills and manipulative abilities [3], [5]. Often supported by neurofeedback [3], [10], motor imagery is related to attentional processing, as it is still a mental practice [25], [26]. Understanding the mental effort involved in such tasks is crucial for optimizing training protocols, as it reflects the subject's allocated capacity to satisfy the task demands [23]. In this study, the discriminative features of mental effort during motor imagery tasks using a few-channel-based EEG measurement system Data were labeled under the assumption that mental effort was lower during the first and higher during the sixth run. According to the time-based resource-sharing model [27] [28], the persistence of cognitive task execution over time results in progressive cognitive fatigue. The occurrence of a cognitive fatigue condition results in a decrease in task performance or an increase in the effort required to maintain a high level of performance. Actually, the performance during a task execution may be affected by the levels of engagement or distraction [29]. The persistence of high level of performance during the task makes it possible to rule out the advent of distraction and ascertain a continuous application of the subject to the proposed task over time. Therefore, in the time-based resource-sharing model framework, the hypothesis that as time passes, the mental effort expended by the subject increases can be assumed.

The SFS was effective for selecting a small number of relevant features (5 features extracted per 8 channels) from the total of 40 EEG features extracted to classify mental effort. The good accuracy achieved in both groups (82.1 % and 84.0 % for control and neurofeedback group, respectively) confirms that relevant information can be acquired from a few sources, regardless of the classifier used. This result confirms that mental effort can also be monitored through the use of highly wearable systems based on a few channels. Furthermore, the spatial region found to be most informative on mental effort is the frontal region. This is consistent with several studies stating how the frontal lobe is associated with cognitive processes, including complex cognitive processes [15], [16], [18]–[20]. The small improvement in predicting mental effort in the neurofeedback group is consistent with previous work that showed that mental effort increases when neurofeedback is provided [30], [31]. However, considering that feature learning occurred only on the control group, such a high accuracy on the neurofeedback group highlights that the phenomenon is more discriminable. Finally, the study has some limitations. Firstly, it was confined to a single experimental session to mitigate participant variability effects. Future studies should encompass multiple sessions to assess robustness. Moreover, the use of tasks more suited to surgical scenarios and the comparison of different EEG cap densities could provide insights. Future investigations could extend the proposed methodology to neurosurgeons performing motor imagery tasks similar to their surgical routines and perform a multi-channel cap comparison to strengthen the validation of this wearable EEG-based study.

VI. Conclusions

The study demonstrated the feasibility of an EEG-based method for assessing the level of mental effort during motor imagery tasks supported by neurofeedback. The solution can be used to improve the training of novice surgeons involved in minimally invasive surgery by adapting the training on the basis of mental effort detected. For all classifiers, SFS identified four features for maximizing accuracy. MLP resulted in higher performance, with an average accuracy of $82.1\ \% \pm 8.7\ \%$. The selected features were: (i) theta-to-alpha ratio on Fz channel, (ii) beta-to-delta ratio on O1 channel, (iii) theta-to-beta ratio on FP1 channel, and (iv) (theta+alpha)/beta on FP1 channel. The EEG features identified by the SFS are consistent with those related to mental effort reported in the literature. These features were used in the mental effort classification of the neurofeedback group, employing the MLP classifier, achieving an average accuracy of $84.0\ \% \pm 6.8\ \%$. This finding is in line with the results of the NASA-TLX questionnaire, namely that subjects supported by neurofeedback show slightly greater mental effort with respect to the group without neurofeedback. Future research will be directed towards the utilization of alternative feature selection algorithms capable of navigating the feature space without becoming trapped in local maxima.In particular, meta-heuristic approaches such as the Salp Swarm Algorithm, which has recently been shown to be effective for EEG feature selection in motor imagery [32], will be tested. Additionally, the identification of a "mental effort" threshold after which the surgeon should stop the current action will be pursued. The classification binary choice, i.e., low vs high mental effort, represents a first step towards the adoption of a metric scale with a finer resolution. The greater the number of classes, the greater the resolution of the classifiers in discriminating the levels of mental effort. In this way, a classifier trained on a single subject data could recognize the personalized alert threshold corresponding to a specific class. Finally, integration of the proposed method into the adaptive system for neurosurgeon training and its experimental validation will be pursued.

Acknowledgments

This work was carried out as part of the "ICT for Health" project, which was partially supported by Italian Ministry for Universities and Research (MUR) under the grants FIT4MEDROB (PNC0000007) and "INTENSE" project, which was financially supported by the Italian Ministry of Enterprise and Made in Italy, (MIMI). The authors thank Salvatore Piccolo for his contribution to the state of the art of this work.

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