Detection of Vigil And Fatigue States During The Execution of Laparoscopic Tasks Based On EEG Patterns

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Abstract

Fatigue decreases performance in several professional activities. Fatigue can lead to commit technical mistakes which consequences might be lethal, such as in health area, where a surgical error due to the absence of rest can provoke the patient death. Therefore, this study aims to detect vigil and fatigue (due to lack of sleep) states in medical students through the classification of electroencephalographic (EEG) patterns. The EEG signals of 18 physician students were analyzed within theta band (4 - 8 Hz) over front-central recording sites, and alpha band (8 - 13 Hz) rhythms over temporal and parieto-occipital recording sites during the execution of laparoscopic tasks before and after their medical duties. The EEG signal processing pipeline consisted in pre-processing based on individual component analysis, absolute band power estimates, and Support Vector Machine classification. The F-score to differ between vigil and fatigue states was 90.89%, where the first class was slightly more identifiable reaching a sensitivity of 90.18%. Based on this outcome, the detection of fatigue in medical students while their laparoscopic training seems achievable and feasible to diminish technical mistakes that could be lethal in health area. For this purpose, EEG recording are provided.

Introduction

It cannot be assumed that all people who undertake a task do it in an alert state. The lack of vigilance is denominated fatigue. According to [1], fatigue is a transitional state between vigil and sleep that is characterized by the absence of alertness and the deterioration of mental or physical performance. Several professions that involve high workload and stress such as aviation or surgical intervention demand a high alert state to avoid lethal mistakes. In health area, medical errors are the main cause of injuries to patients in hospitals [2]. A medical error is defined as: (1) the failure of a planned action, (2) the process to be completed as intended (execution error) or (3) an improper planning to achieve the target. Besides, omission errors are also considered medical errors since a lack of action can cause the patient harm [3]. According to [4, 5], the average death rate due to medical errors was 251,454 per year in 1999 based on the report of the Institute of Medicine, and extrapolating the amount of hospital admissions in the United States in 2013. Thus, medical errors are the third leading cause of death. These errors do not only inflict the patient harm, but also the hospital economy. The cost of medical errors is estimated to be between $17–29 billion of dollars per year, including profits and additional costs of medical treatment, and contributing to the delay in progress of a better health sector [3]. It is not surprising that this rate of medical errors exists in the health sector, due to the complexity of medical practice, and the high quantity of surgical interventions that are carried out daily. Patients in intensive care received an average of 178 activities/procedures per day. A rate of 1.7 errors per day indicates that the hospital staff achieves a 99% efficiency level. However, the 1% failure rate is significantly higher than the tolerated in the industry, specifically in high-risk sectors such as aviation and nuclear plants. To clearly understand this problem, if one had the same percentage error in aviation, one would have two unsafe or failed landings per day at the Chicago airport [6].

Therefore, it is highly important to assess the cognitive states and the mental workload effect on human beings during their work in order to minimize errors of execution, planning or omission [7]. One of the most common techniques to evaluate mental states in a non-invasive way is to analyze electroencephalography (EEG) activity. EEG technique registers the neuronal electrical activity, and reflects the modulation of such activity due to external (e.g., sensory or motor) and internal (e.g., mental load, cognitive states such as vigil or fatigue) stimuli [8].

It has been found that while a human being is awake, the power spectral density of EEG signals in frequencies between 6.25 and 9 Hz (theta and alpha) grows constantly as the degree of sleep deprivation increases [9]. It has also been shown that the transition between vigil and fatigue is reflected as a modulation of the EEG signals from alpha to theta band. This means that a reduction of EEG activity in alpha band may be an indicator of drowsiness, as long as the eyes are open, since the distinction between wakefulness and sleep with closed eyes does not show the previous behavior. This can be attributed to the immediate replacement of alpha by theta band activity [10, 11]. In [12], it was proposed that this phenomenon occurred because participants fell asleep when they closed their eyes to pay the sleep debt they have acquired. Other investigations have focused on characterizing electroencephalographically the effect of sleep deprivation on cognitive and physical performance. For instance, in [13], it was reported that continuous periods of inadequate sleep can develop hypertension or an inefficient response to intense exercise. In [14], the transition between vigil and fatigue in drivers was characterized by EEG recordings. Authors demonstrated that alpha and theta bands over the parietal and occipital lobes provide enough information to detect the transition in automotive situations. In [15], it was found that there were no behavioral (subjective measurement of sleep based on the Karolinska scale [16] and driver performance) or physiological (duration of blinks) changes until the driver considered himself drowsy. Similarly, supervised and unsupervised methods of automatic learning have been applied to detect and predict the levels of drowsiness in several daily life situations [3, 17, 18].

Therefore, this work seeks to evaluate the performance of junior surgeons during laparoscopic training in two conditions: vigil and fatigue states. According to the American Society of Colon and Rectal Surgeons, the laparoscopic surgery is defined as a minimally invasive surgery [19]. This technique has been a primary skill to be acquired in junior surgeons since laparoscopy surgeries diminish pain experience in patients, have a rapid recovery, and the healing process is more efficient. The most commonly used validated test to measure different dimensions of laparoscopic skills was designed by Dr. Gerald Fried [20]. This test consists in five tasks: (1) moving rubber rings on a pegboard, (2) cutting a circle on a gauze pad employing laparoscopic forceps and endoscopic scissors, (3) tying a loop to one of the ends of a weave with laparoscopic instruments and a pre-tied ligature, (4) performing an extracorporeal suture with laparoscopic instruments and tying it, cutting the remaining thread and finally, (5) suturing intracorporeally following the same strategy as the fourth task. Hence, the aim of this project is to analyze EEG signals of 18 junior surgeons, undertaking the five tasks proposed by Dr. Fried before and after their 24h-duty in order to automatically detect their vigil and fatigue states reflected during their laparoscopic training. This project moves towards including human factors in medical trainings to improve the skill acquisition, and thus diminishing technical mistakes during surgeries.

Methods

2.1 Sample

Twenty-one students were recruited from the School of Medicine at Tecnológico de Monterrey. The criteria for exclusion were: (1) physical impairments that prevented the execution of laparoscopic exercises, (2) seizure records or brain disorders, (3) intake of drugs that interfere with brain activity such as benzodiazepines or anticonvulsants, and (4) history of head trauma. The study was previously authorized by the Ethics Committee of the School of Medicine at Tecnológico de Monterrey. All volunteers signed an informed consent form, authorizing their participation in the study.

2.2 Equipment

The Emotiv EPOC headset was used to record EEG activity. This headset has 14 EEG channels, 7 of them are over each hemisphere, positioned on the prefrontal lobes (AF3, AF4), frontal (F3, F4, F7, F8, FC5, FC6), temporal (T7, T8), parietal (P7, P8) and occipital (O1, O2) according to the International System 10/20 [21]. The headset was connected via Bluetooth, configured to record at 128 Hz into a bandwidth from 0.01 to 43 Hz. The referencing sites (CMS, DLR) were over two mastoids. Additionally, Ethicon Endo-Surgery (Johnson & Johnson's) simulation equipment was used to undertake the laparoscopic techniques.

2.3 Experimental Procedure

First, the candidates were informed about the objective of the research and the steps of the experimentation. Once their doubts were clarified, all who agreed to participate in the study signed a written consent form. Then, they attended twice to the Medical School Skills Center to carried out the five tasks designed by Dr. Fried. The first session was held one hour before their medical duty, and the second one was after it. Each session lasted between 30 and 60 minutes. In each session, it was explained that they would perform five basic laparoscopic tasks, involving visuospatial and somatosensory/cognitive processing skills (see Fig. 2). In addition, they were instructed to complete each task along a specific time. Before starting the laparoscopic training, the Epoch Emotiv headset was collocated and tested to verify its correct operation. At the end of the test, the participants were thanked and informed that all data would be treated with absolute confidentiality, and would be used exclusively for research purposes. The experimental procedure is illustrated in Fig. 1.

2.4 Laparoscopic Tasks

The laparoscopic tasks performed by the volunteers are illustrated in Fig. 2. These are described below:

Peg transfer (Fig. 2A). This activity consists of transferring the previously positioned rings from the dominant side of the user to the non-dominant side. The camera must be adjusted so that the user has a complete view of the working board. The rings should be grasped with the non-dominant hand, and transferred with the dominant hand. Each transfer has a maximum time allowed of 300 seconds. The

transfer time was measured from the time the target ring was touched until it was released on the corresponding pin. The measurable variable was the time required to complete the activity.

Precision cutting (Fig. 2B). The activity consists of cutting a circle previously drawn on a gauze in the shortest time possible, considering 300 seconds as the maximum time to complete the task. At the beginning of the task, the Maryland dissector is held in one hand, and the endoscopy scissors in the other one. During the task, both instruments can be transferred between the hands.

Ligating loop (Fig. 2C). For this activity, a tissue is provided with 3 terminals, where the central terminal has a mark at the end of it. With one hand the Maryland dissector is held, and with the other one, a pair of tweezers is held with a ligature that has a pre-tied loop at one end. The objective of the activity is to place the pre-tied loop along the center end mark. Once the loop is positioned, it must be adjusted around the center, and secured it with a knot. Finally, the ligature is cut to release it from the tweezers. There is a penalty if the ligature is outside of the center end mark. The time of the activity is recorded until the ligature is cut. The maximum time allowed is 180 seconds.

Suture with intracorporeal node (Fig. 2D). This activity has a maximum time allowed of 600 seconds. A tube with two holes (which is fixed with Velcro) is provided. The target is to introduce a thread that crosses the two holes to make a knot that ties the two holes together. Once the first knot is made, two more must be made. For this activity, the ties are made inside the trainer, this means that the laparoscopic instruments should not be removed.

Suture with extracorporeal node (Fig. 2E). This activity has a maximum time allowed of 420 seconds. The materials are the same as in the previous activity, and the objective is the same. The only difference is that the ties for the knots are made outside the trainer.

2.5 EEG Analysis

From the sample of 21 volunteers, three records presented important distortions that made the data unrecoverable for analysis, therefore only 18 records were analyzed. It is important to highlight that one of the most important challenges in the study of neurophysiological activity in real scenarios, as it is the present case, the signal distortion is generated by internal (e.g., electrophysiological activity originated by eye, muscle and/or heart movements), and external (e.g., electric current at 60Hz) noise sources, and the kinetics related to the functions that the individual performs while his behavior is observed [22]. In Fig. 3, an example of a discarded record is presented.

For signal analysis, the free library for MATLAB known as EEGLAB was used [23]. This analysis was performed in four stages: (1) pre-processing, (2) processing, (3) feature extraction, and (4) classification. Each of these stages is described below. Preprocessed signals can be downloaded from https://doi.org/10.6084/m9.figshare.12559547.v1.

2.5.1 Pre-processing

For the pre-processing, the signals were filtered in a bandwidth (BW) between 0.5 and 30 Hz, applying a sixth order IIR filter. With this BW, the gamma band (> 30Hz), which is difficult to capture by EEG due to its high frequency and low amplitude, was discarded. Subsequently, a visual inspection of the records was performed to eliminate signal segments that showed significant disruptions such as (1) sudden body movements; (2) random and intermittent disconnections of the EEG electrodes; and (3) electrical muscle activity (mainly facial activity). Finally, independent component analysis was applied to identify, and eliminate continuous artifacts such as (1) blinking and eye movements (see Fig. 4), and (2) electrocardiographic activity.

2.5.2 Processing

To differentiate between wakefulness and fatigue with EEG records, there are different proposals [23, 24]. Recently in [25], it was proposed to estimate the arousal level analyzing the theta-band (4–8Hz) in the front-central channels and the alpha-band (8–13Hz) in the occipital and parieto-temporal channels. This last methodology was chosen because the authors detected a vigil state in real time.

The processing consisted on applying a Butterworth IIR filter of eighth order in the channels, and BWs proposed in [25]. Afterwards, the signals were normalized through the bipolar sigmoidal method, and their power was estimated based on a one-second window segmentation with 50% overlapping. Finally, the segment powers were averaged to obtain a single absolute value in two BWs: (1) theta and (2) alpha.

2.5.3 Feature Extraction

From the signal processing, the absolute spectral powers in theta and alpha were estimated. The feature extraction was performed as follows: AF3, F7, F3, FC5, FC6, F4, F8, and AF4 for theta, and T7, P7, O1, O2, P8, and T8 for alpha. In previous researches [24, 26], it has been shown that the parietal and occipital lobes provide the most information to differentiate between vigil and fatigue. Therefore, two average absolute powers (theta and alpha) were obtained for the EEG channels respectively. That is, 14 features per volunteer for each session (before and after the duty), and a total of 1610 observations were obtained.

2.5.4 Classifier Selection

Five classifiers were compared: (1) decision tree, (2) linear discriminant analysis, (3) logistic regression, (4) support vector machine (SVM), and (5) nearest neighbor. In Table 1, the results of each classifier are shown. As can be seen, the SVM with a cubic kernel was the classifier that achieved the best performance. For this classifier, its confusion matrix is shown in Fig. 5, where the "pre" class (orange color, negative) refers to the vigil state, while the "post" class (blue color, positive) refers to fatigue. The observations of the selected features were 70% for training, and 30% for testing. The evaluation parameters of the classifier performance were the following: accuracy, precision, sensitivity, specificity, and f-score.

Table 1. Comparison of five classifiers

Type	*Classifier*	*Accuracy*
Decision tree	Fine tree	72.4 %
Linear discriminant analysis	Quadratic discriminant	82.3 %
Logistic regression	Logistic regression	71.2 %
SVM	**Cubic SVM**	**90.7 %**
Nearest neighbor	Fine KNN	85.0 %

2.6 Statistical Evaluation

In addition to assess the performance of the EEG pattern classification, the execution times of the five laparoscopic tasks performed by each participant before and after his medical duty were estimated. The execution times per task were statistically compared by applying a t-test, considering a p-value greater than 0.05 to reject the null hypothesis.

Results

To identify singularities that could characterize vigil and fatigue states during the performance of laparoscopic tasks, the spent time to complete each laparoscopic task was recorded for each volunteer, and the degree of (1) accuracy, (2) precision, (3) sensitivity, and (4) specificity was evaluated to differentiate between EEG patterns in each state.

3.1 Average execution times for laparoscopic tasks

The average completion times for each task are shown in Table 2. As it is shown the activities 2, 4 and 5 involved a longer time of completion ($t > 15$ s) when they were executed after the duty. However, activity 1 was performed in the same average time in both conditions (pre- and post-duty). Moreover, activity 3 was performed in less time after the medical duty. In addition, no significant difference ($p = 0.269$) was found in any task before and after the duty.

Table 2
Average time to execute each laparoscopy task proposed by Dr. Gerald Fried

	Number and type of task				
	1	2	3	4	5
Maximum time (s)	*A*	*B*	*C*	*D*	*E*
	1800	*300*	*180*	*600*	*420*
Pre-duty	241 ± 100	246 ± 105	71 ± 47	226 ± 136	310 ± 220
Post-duty	241 ± 91	261 ± 94	55 ± 37	249 ± 201	371 ± 205
Difference	**0**	**+ 15**	**-16**	**+ 23**	**+ 61**

3.2 Evaluation of Identification between Vigil and Fatigue

In Fig. 6, the confusion matrix of the cubic SVM is presented by classifying the EEG patterns into two classes: vigil (pre) and fatigue (post). Table 3 shows the performance of this classifier. According to the implementation requirements for passive brain-computer interfaces, an accuracy of equal to or greater than 70% should be achieved [27]. The reached performance exceeds by 20% the standard requirement for a system whose objective is to determine an individual mental state in real time. From the table, it is possible to observe that the difference between vigil and fatigue was relatively balanced since few false negatives and positives were obtained (sensitivity = 90.18%). Note that vigil was relatively easier to identify, due to the percentage of false positives compared to true negatives (specificity = 91.33%) was lower.

Table 3
SVM Cubic Classifier Performance

Parameter	***Percentage***
Accuracy	90.7%
Precision	91.63%
Sensitivity	90.18%
Specificity	91.33%
F-score	90.89%

Discussion And Conclusion

Laparoscopy is a minimally invasive surgical intervention that requires high proficiency skills such as depth perception and hand-eye coordination. In addition, surgeons must develop cognitive skills such as attention, information processing, storage and feedback of information, in order to make the best

decision at the right time, and execute the necessary movement for the patient well-being [28]. These skills are affected by lack of rest (a common practice in the medical field). For this reason, this study aimed to identify the states of vigil and fatigue due to lack of sleep, through the analysis of EEG activity. Fatigue state in surgeons can lead to execute irreparable surgical errors in patients. Hence, there is an opportunity to eventually implement systems that alert about the current state of the surgeon, and thus prevent accidents.

EEG activity is sectioned into various rhythms or frequency bands: gamma (> 30 Hz), beta (13–30 Hz), alpha (8–13 Hz), theta (4–8 Hz) and delta (1–4 Hz) [29]. In particular, theta and alpha bands are related to learning processes. Theta band has been associated with memory and cognitive tasks; synchronization of this rhythm is due to the increase of the cognitive effort during the execution of an activity. In general, this band is present over the frontal lobe, which is associated with visual perception [30, 28]. On the other hand, alpha band is related to the level of attention, thus desynchronization of this rhythm is related to inhibitory action to enable the processing of information [28]. On this evidence, the present study seeks to analyze the amplitude changes of EEG signals in theta and alpha bands during five laparoscopic training tasks of 18 junior surgeons, before and after their duties to differentiate between vigil and fatigue states. It was found that the required time to perform the laparoscopic tasks did not change significantly before (vigil) and after (fatigue) the on-call (statistically speaking). However, the central trends in execution times were greater or equal after the duty, except for the ligating loop activity (Fig. 5). This means that on average, junior surgeons in training spent more time to perform the same task due to lack of sleep [31].

On the other hand, the power changes of the spectra of the EEG signals in theta and alpha bands were enough to differentiate between wakefulness and fatigue states (accuracy = 90.7%). That is, 9 out of 10 vectors of EEG features recorded in real time could be properly identified within the correct state: wakefulness or fatigue. The results of the present study contribute with a first attempt to identify the mental states of physicians in training under real conditions. It should be noted that the experimental procedure was not implemented in a laboratory under controlled conditions, but in the Skills Center, where physicians are trained to master the technique of laparoscopy. Furthermore, the presented results can be improved with other analysis strategies. For example, in [32], authors classified 40 different signals from each electromagnetic disturbance (320 in total), which interfere with the normal operation of electrical power systems by using the Hilbert-Huang Transform with an accuracy of 94.6%. Another improvement can be the use of neural networks as a classification phase. As a preliminary analysis, three different neural networks were used:

1. InceptionV3 Model implemented in Python using Keras applications. The architecture can be consulted in [33], its weights were loaded from ImageNet to have a pre-trained network, and the signals were converted to standardized images, and rescaled to have a size of 299x299x3.
2. *Model that concatenates the feature vectors of the VGG19 and ResNet50 models.* The model architecture can be seen in [34], only AlexNet was replaced by ResNet50 as it was the one available in Keras applications. Keras applications was used for both models, and the weights were imported

from ImageNet. Each image was normalized and rescaled to 227x227x3 to feed data in the concatenated model.

3. *5-Fully-Connected layer Neural Network* [35]. The first layer had 500 units, the second one had 290 units, the third one had 79 units, the fourth one had 59 units, and a single output. The network iterated 10000 times, and the learning rate parameter was 0.0075.

Using the same characteristics, the same number of observations, and the same distribution of data (70% for training and 30% for testing), the performance achieved of the three neural networks used in the preliminary analysis did not exceed 73%, as shown in Table 4.

Table 4
Classification of three neural networks

Neural network	*Accuracy*
Inception V3	66.33%
VGG19ResNet50	50.57%
5-Fully-Connected	73.08%

The presented accuracies are low, practically the networks are guessing if the junior surgeon is in a state of vigil or fatigue, except for the 5-layer neural network totally connected that showed the best result. This is because the first two networks detected a high variance in data. To improve the results, it is necessary to increase the number of observations and/or include regularization parameters to the network, which implies a higher computing time. The last network could be optimized by adding more layers, or by training the network for a longer period, what would become unfeasible for the purposes of this research.

The findings of the present research broadly support the work of other studies in this research area. In [36], authors classified manual movements (left and right) of experienced and novice residents, after the use of an obstetric clamp. They obtained a classification of 99.1% with the employment of a recurrent neural network (RNN), along with the long-term-short-term memory (LSTM). In [37], authors were able to classify EEG signals between wakefulness and fatigue states, reaching an accuracy of 96.28%. The methodology proposed by [38] achieved 99.61%. In [39], it was found that stress (analyzed with alpha band records) is a factor that negatively influences the execution of surgical practices. In [40], authors analyzed fatigue in surgical practices, by repeating the peg transfer task. They concluded that effectiveness in surgical practice is not determined by the time taken to perform an operation, but by the absence of errors. These studies lead us to propose that the execution time of the laparoscopic tasks reported in this study (Table 2) can be eventually used to correlate the effectiveness and execution time of each task, affected by states of wakefulness or fatigue.

In conclusion, sleep-induced fatigue generates power changes of identifiable EEG signals in theta (front-center area) and alpha (temporal and parieto-occipital areas) bands in trainee physicians during their

laparoscopic training. The EEG analysis was based on differentiation between absolute power values through a cubic SVM classifier.

Declarations

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Compliance with Ethical Standards

Research involving Human Participants and/or Animals

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Conflicts of interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Ethics Approval

The experimental procedure was formerly approved by the Ethical Committee of the National School of Medicine of the Tecnologico de Monterrey.

Consent to participate

All participants were informed about the experimental procedure and signed a consent form.

Consent for publication

Authors declare no conflict of interest and agree to publish the present work.

Availability of data and material

Preprocessed EEG signals of the 18 junior surgeons undertaking the five laparoscopic tasks can be downloaded from https://doi.org/10.6084/m9.figshare.12559547.v1.

Code availability

Not applicable.

Authors' contribution

Yeremi Pérez elaborated the state-of-the-art, generated the discussion, translated the whole manuscript, and coordinated the team work. Roberto Borboa-Gastélum preprocessed the EEG signals, extracted the EEG feature, and undertook the first runs of the classification process. Luz María Alonso-Valerdi proposed and supervised the EEG analysis, wrote the first version of the manuscript, and supervised and corrected the last version of the manuscript. David I. Ibarra-Zárate designed and implemented the presented classification process, and revised the manuscript. Eduardo A. Flores-Villalba, and Ciro A. Rodríguez-González conducted the field investigation in the School of Medicine, and provided the EEG information.

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Figures

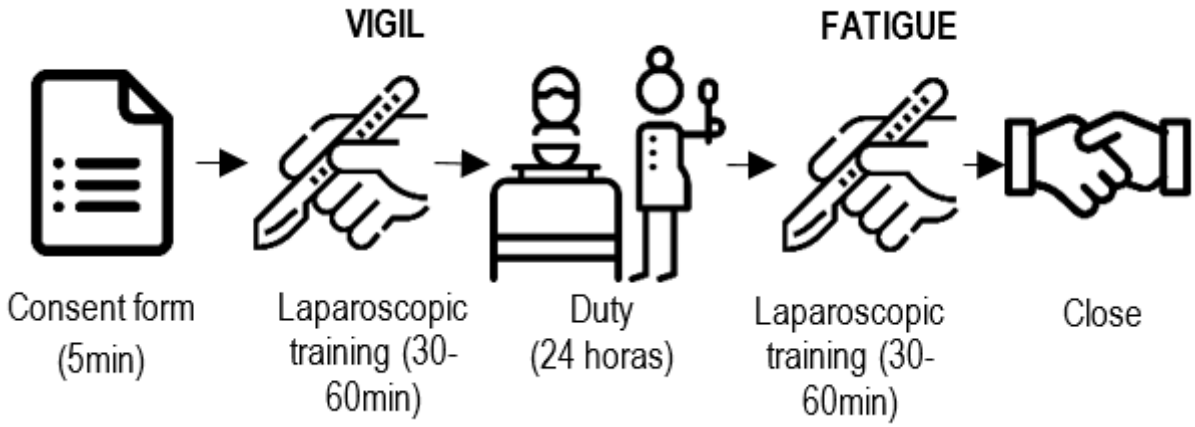

Figure 1

Study planning: Experimental procedure to collect EEG data during laparoscopic training in a waking state and sleep-induced fatigue.

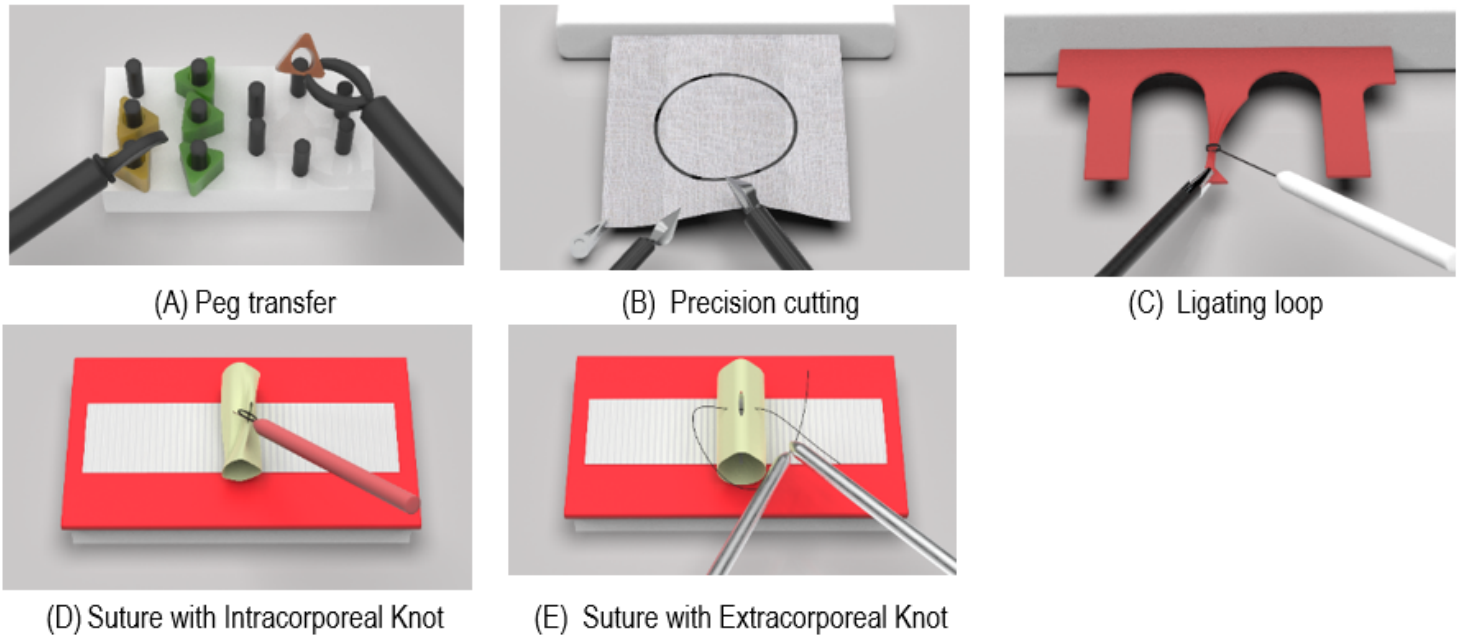

Figure 2

Training tasks to acquire the laparoscopic technique proposed by Dr. Gerald Fried [20].

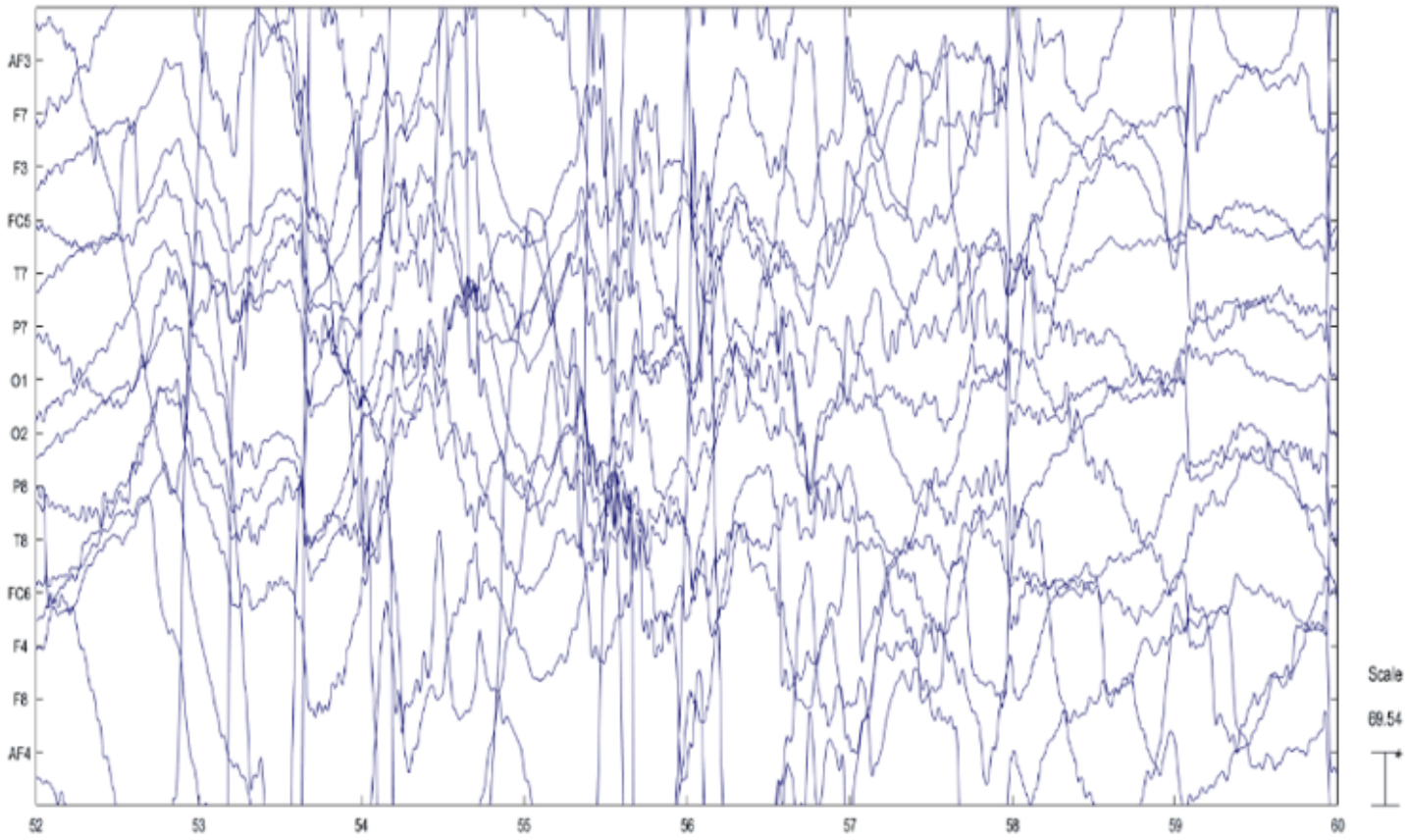

Figure 3

Raw EEG signals recorded from one of the volunteers during the laparoscopic test before performing their respective medical duty.

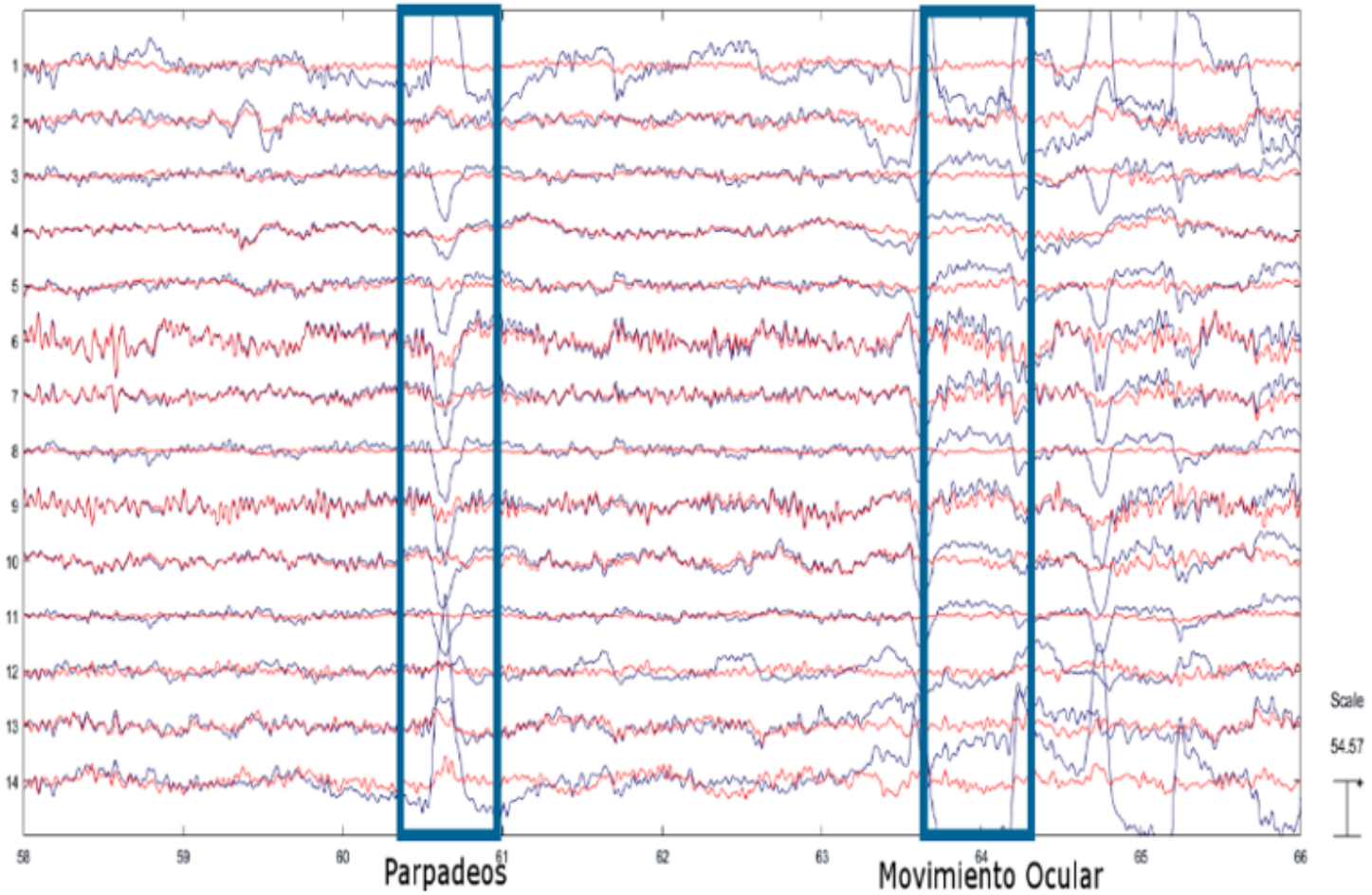

Figure 4

Comparison of EEG signals before (blue) and after (red) pre-processing. Potentials generated by blinking and eye movements can be observed clearly inside the frames.

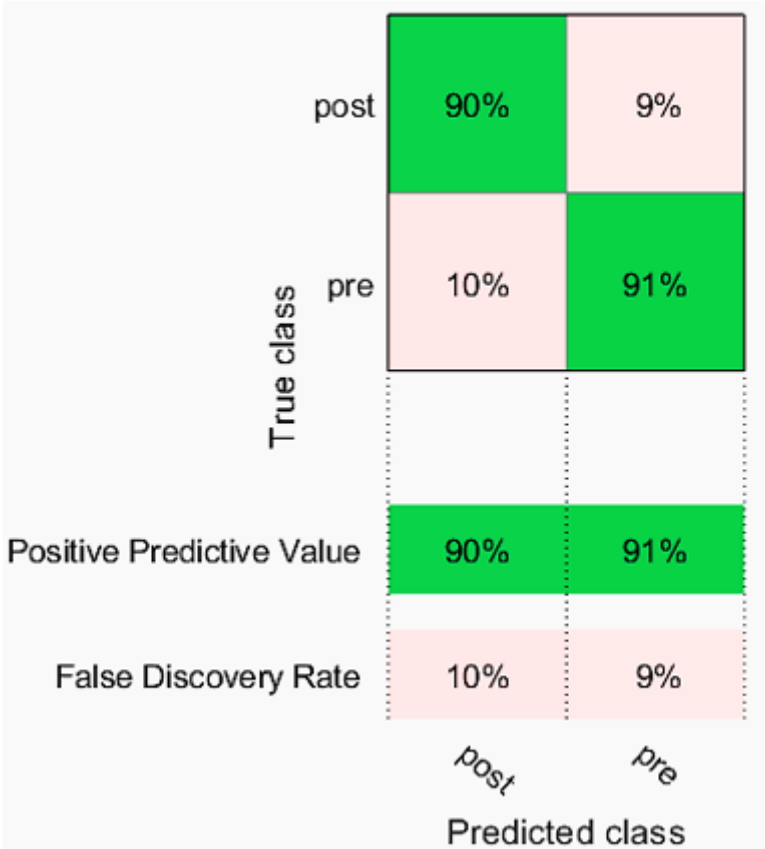

Figure 5

SVM performance of a cubic classifier to differentiate between fatigue (post) and vigil (pre).

Image not available with this version

Figure 6