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A Practical Case of Learning Muscle Fatigue Based on a sEMG Signal Using Bitalino Kit

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***Abstract*—This paper explores the use of technology in teaching biosignal processing, specifically focusing on the flipped classroom model and the BITalino kit. The flipped classroom allows students to learn at their own pace before coming to class, while the BITalino kit provides an affordable and versatile platform for acquiring and analyzing biosignals like electromyography (EMG).**

The paper details a case study where students used the BITalino kit to classify EMG signals as fatigue and non-fatigue. The methodology involved acquiring EMG signals from the quadriceps muscles during an incremental exercise test, followed by signal processing, feature extraction, and machine learning classification.

The study demonstrates the effectiveness of the flipped classroom and BITalino kit in enhancing student learning and engagement with biosignal processing. The developed machine learning model achieved an accuracy of 90% in classifying muscle fatigue, highlighting its potential for applications in sports science, rehabilitation, and ergonomics.

The paper concludes by emphasizing the importance of integrating new technologies into engineering education to create immersive learning experiences and equip students with the necessary skills for the evolving demands of the industry.

***Index Terms*—Biosignal, flipped classroom, biomedical engineering, learning experience**

I. INTRODUCTION

Technology for teaching in engineering has become increasingly important in higher education, providing better learning opportunities for students [1]. In this context, engineering educators need to be proficient in both educational technologies and didactics to effectively integrate them into the classroom.

The flipped classroom model is an effective way to improve student learning. In this model, students access learning materials, such as videos, infographics, and other resources, before class. This allows them to learn at their own pace and come to class prepared to engage in discussions and activities. The flipped classroom has gained visibility and relevance, especially during the COVID-19 pandemic, demonstrating the effectiveness of technology-driven models to improve student motivation and learning [2]. This model has also been shown to be effective in engineering education [3] [4].

In engineering, teaching classes becomes increasingly complex, particularly in the area of biomedical engineering, where knowledge of various fields like physiology and anatomy is crucial. Additionally, students need to grasp mathematics and algorithms for manipulating biosignals and their filters using biomedical signal processing [5]. The diverse and complex nature of biomedical signals necessitates that students understand and utilize advanced tools for signal acquisition, filtering, and processing [6], [7].

The mathematical component of biomedical signal processing creates a significant challenge for students, as they must grasp complex mathematical concepts and algorithms used in signal processing, such as higher-order statistical and tensor decompositions [8] [9]. Furthermore, the design of filters in biomedical signal processing demands a deep understanding of signal processing theories, methods, and algorithms for tasks such as noise reduction, restoration, and pattern recognition. Even the integration of artificial intelligence (AI) in biomedical signal processing poses challenges related to the collection and processing of datasets to develop reliable AI models [10].

Due to the complexities of teaching biomedical signal processing, the Introduction to Biomedical Signals (ISB) course at a Peruvian university was adapted to the flipped classroom model [4]. This course develops the knowledge necessary for processing signals from educational platforms for biomedical signal acquisition. Topics covered include the acquisition, filtering, and processing of biomedical signals such as electromyography (EMG), electrocardiography (ECG), and electroencephalography (EEG).

The relevance of sEMG lies in its ability to provide accurate information about the production of force in skeletal muscle [11]. It is an integral and effective tool in the management and monitoring of muscle fatigue in sports and rehabilitation contexts [12], [13], [14].

Electromyography (sEMG) plays a crucial role in assessing one of the key contributors to physical performance limitations: muscle fatigue. This phenomenon, is characterized by difficulty in executing physical activities due to an inability to sustain essential muscle force [15].

On the one hand, exercise itself influences fatigue through mechanisms like energy depletion, metabolite accumulation, and changes in muscle fiber recruitment patterns. Daily life also contributes, with factors like sleep quality, nutrition, and overall stress levels impacting fatigue susceptibility. Understanding how these diverse elements influence sEMG signals is crucial for accurately assessing fatigue and designing effective interventions [16].

By delving deeper into the intricate relationship between sEMG and muscle fatigue, we can unlock valuable insights into improving performance, optimizing training strategies, and even managing chronic fatigue conditions. Research efforts focusing on interpreting sEMG signatures in the context of these various influencing factors hold immense potential for revolutionizing our understanding of muscle function and optimizing human health and performance across various domains [17]. In this paper, we present a case study of a group of students who used sEMG to classify signals as fatigue and non-fatigue.

II. Bitalino and its application to learn biomedical signals

The BITalino kit, developed by PLUX Biosignals, offers several advantages for the learning of biosignals. Firstly, the kit provides a versatile platform for biosignal acquisition and connectivity, incorporating sensors such as photoplethysmography (PPG), electromyography (EMG), and accelerometers (ACC), offering a portability advantage to users. Fig 1 shows the Bitalino board and its sensors it has. This portability enables hands-on learning experiences, where students can engage directly in the collection and analysis of biosignal data, fostering a deeper understanding of physiological concepts. This allows for the measurement of various biosignals, facilitating a comprehensive understanding of physiological processes. Furthermore, the BITalino kit is designed to be adaptable to different needs, making it suitable for both educational purposes and research applications that require advanced biosignal analysis. This enables students and researchers to explore complex data patterns and develop innovative applications [26].

Moreover, the BITalino kit's versatility extends to its connectivity options, allowing for seamless integration with other devices and software. This enables students to explore interdisciplinary applications of biosignal analysis, such as integrating biosignal data with machine learning algorithms for pattern recognition. Additionally, the kit's user-friendly interface and software make it accessible to students with varying levels of technical expertise, allowing them to focus on learning and experimentation rather than technical challenges. The name of its software is opensignals and it has a very of functionalities such as acquiring, pre-processing and visualizations [27].

Another key advantage of the BITalino kit is its affordability, making it accessible to a wider range of educational institutions and students. This affordability lowers the barrier to entry for students interested in exploring biosignal analysis, enabling more students to gain practical experience in this field. Additionally, the kit's open-source nature encourages collaboration and innovation, as students and researchers can share their work and build upon each other's projects.

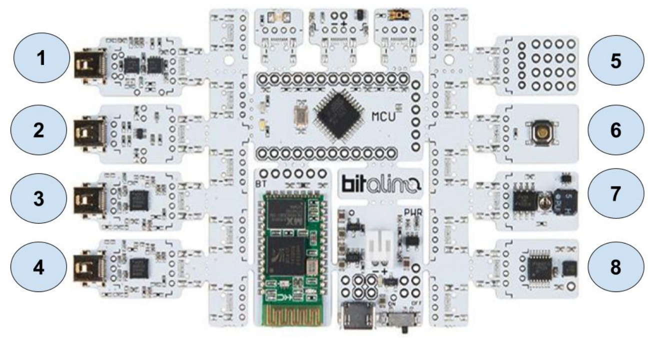

Fig. 1. Sensors included in Bitalino Kit. (1): EEG, (2): EDA, (3): ECG, (4): EMG, (5): Free, (6): Button, (7): Buzzer, (8): Accelerometer.

III. Methodology

The present document aims to present the experience of implementing a practical case for learning sEMG signal based on the Flipped Classroom didactic strategy. To do this, the practical case was an activity that involved the acquisition of EMG signals to evaluate muscle fatigue in the quadriceps muscles. Before the day of the activity, two activities were carried out: 1) Audiovisual material and scientific articles were sent to the students to familiarize themselves with the terminology, and 2) A theoretical class was held to discuss the videos and scientific articles sent.

Finally, the practical laboratory session was conducted with a group of 5 students. The procedure began with a 5-minute body warm-up consisting of stretching exercises. Subsequently, the skin was cleaned with alcohol, and then the electrodes were placed, ensuring that the skin area was free of hair to avoid interference with adhesion. After correctly placing the electrodes, the exercise began. An incremental exercise was performed for 10 minutes on a stationary bike.

The signals were obtained using the Bitalino kit and disposable Ag/AgCl high-adhesion surface electrodes with conducting gel. The surface electrodes for EMG were placed on the vastus medialis and lateralis muscles of the quadriceps, with the patellar tendon as reference. The obtained signals were acquired with a sampling frequency of 1 kHz.

We used Bitalino because it is a tool that works with several biosignals like sEMG. The surface electrodes for EMG were placed on the vastus medialis and lateralis muscles of the quadriceps, and the patellar tendon as reference electrodes. BITalino offers an economical, user-friendly, and versatile

Fig. 2. The stationary bike used for our test

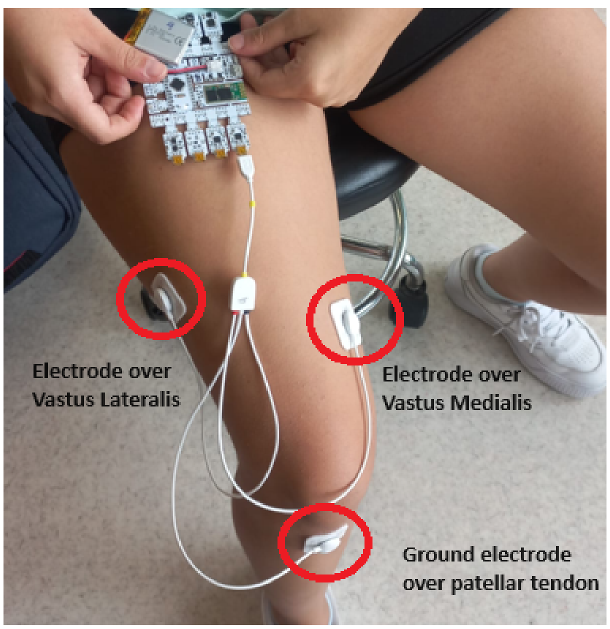

Fig. 3. Bitalino kit ready to acquire the EMG signal

biosignals platform with an open-source design, tailored for both educational and prototyping purposes. It serves as the perfect toolkit for laboratory and classroom use, as well as for developing prototypes and applications involving physiological sensors.

IV. Results

A. EMG Signal Preprocessing

After acquiring EMG signals with a sampling frequency of 1000 Hz, a digital filter was used to optimize their content. To effectively eliminate electrical noise at 60 Hz, common in environments with alternating current, a FIR notch filter was designed. This filter has a cutoff frequency of 60 Hz and a narrow bandwidth of 3 Hz. This configuration allows for the selective suppression of line noise without significantly affecting the EMG signal information.

In addition to the notch filter, a FIR bandpass filter was implemented to retain only the frequency band of interest for EMG analysis. This filter was designed with cutoff frequencies of 6 Hz and 500 Hz. This choice ensures the retention of relevant information related to muscle activity, while simultaneously eliminating low-frequency components (such as motion artifacts) and high-frequency components (such as high-frequency muscle noise).

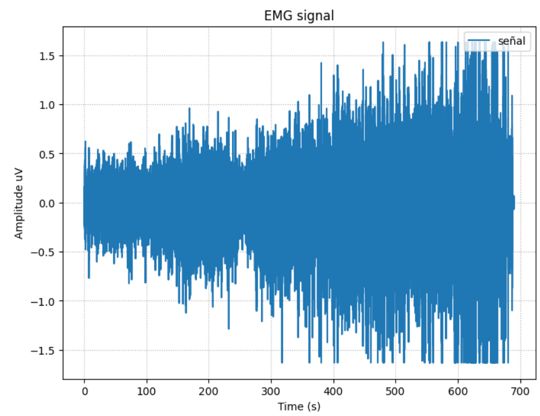

Fig. 4. Example of a EMG signal used in this project

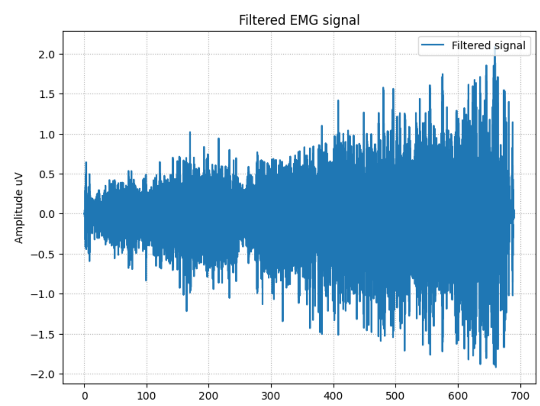

Fig. 5. EMG signal filtered

B. Labeling and Dataset Creation

In this work, we explored an established approach for analyzing electromyographic (EMG) signals in the context of muscle fatigue assessment. This method involves segmenting the EMG signal into specific time intervals, allowing for a focused analysis of muscle activity within distinct periods. To quantify the activity within each segment, we employed the Root Mean Square (RMS) technique, which provides a representative measure of the signal's magnitude. Additionally, a median filter was implemented on the RMS signal to smooth out noise and accentuate the most relevant features associated with muscle fatigue.

Subsequently, we classified the EMG signal into two distinct classes: ”fatigue” and ”non-fatigue”. The segmentation process involved dividing the signal into 8-second intervals, facilitating the evaluation of the temporal evolution of muscle activity. This approach aligns with previous studies in the literature that employed similar strategies to determine the fatigue threshold (PWCFT). In our study, PWCFT identification relied on observing the lowest load that generated a statistically significant positive slope in the amplitude sEMG/time ratio.

To effectively identify significant changes within the RMS signal's evolution, we utilized the Python library ”ruptures.” This valuable tool enabled the automated detection of relevant transitions within the signal, which are crucial for subsequent classification into ”fatigue” or ”non-fatigue” states. The selection of this library was based on its demonstrably strong capability of detecting abrupt changes, offering a reliable means for differentiating between fatigued and non-fatigued muscle activity.

By employing this segmentation and feature extraction approach combined with the ”ruptures” library, we aimed to achieve accurate and robust classification of muscle fatigue using EMG signals. This methodology holds promise for further advancements in biomedical engineering applications related to muscle fatigue assessment and monitoring, particularly in rehabilitation and sports performance analysis.

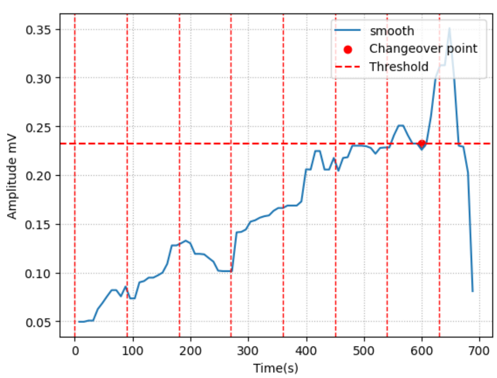

Fig. 6. RMS signal classified by a change point (mV vs seconds)

C. Characteristics extraction and selection

Before proceeding with the extraction of characteristics, a normalization process of the data mean was carried out due to irregularities detected in the signal caused by external factors. This step ensured that the data were uniformly scaled, allowing for a more accurate comparison and analysis.

During the process of extracting characteristics, a range of parameters were calculated with the aim of capturing relevant information for classifying the EMG signal into fatigue or non-fatigue. These parameters included the root mean square (RMS), mean, standard deviation, and amplitude of each time interval window. By analyzing these parameters, we were able to gain insights into the underlying patterns and trends present in the EMG signal.

Following the recommendations found in the literature, we computed the features using wavelet transform to incorporate them as an integral part of the analysis of muscular fatigue. The wavelet transform was applied with 5 levels using the ”db8” main wavelet function. It is important to highlight that a statistical analysis was conducted, focusing specifically on the first two levels of the wavelet transform to extract the most significant characteristics. This approach was chosen due to the recognized importance of the wavelet coefficients as fundamental indicators for analyzing muscular fatigue, providing a detailed and precise representation at various levels of resolution.

The characteristics obtained from both the statistical parameters of the time windows and the wavelet transform were extracted from the signal in both possible states, fatigue and non-fatigue. This comprehensive approach allowed for a thorough analysis of the EMG signal, ensuring that all relevant features were considered in the classification process. By incorporating these features, we were able to develop a more robust and accurate classification model for distinguishing between fatigue and non-fatigue states in the EMG signal.

D. Machine Learning Model Development

During the development phase of the machine learning model, a crucial step involved the normalization of data to ensure the consistency of extracted EMG signal characteristics. This normalization process was vital due to variations in the quantity of data across different signals, guaranteeing a standardized and fair input data distribution for the model. Subsequently, a Random Forest classifier model was employed. The dataset was divided into training (80%) and testing (20%) sets, and the features were normalized using the Standard Scaler method to ensure optimal model performance.

Following the training phase, a thorough evaluation of the model was conducted using the testing set, resulting in a satisfactory and acceptable level of accuracy. The separation of acquired signals into distinct groups for training and testing enabled a detailed analysis of the machine learning model's performance. The model achieved an accuracy rate of 90%, along with 90% sensitivity and 90% specificity, demonstrating its effectiveness and reliability in classification tasks related to EMG signals.

V. Discussions

The teaching of courses focused on learning about biosignals requires the support of technology. A variety of technological tools can be utilized during a class not only to facilitate the practical understanding of complex concepts but also to prepare students for the technical challenges in the field. The use of technologies like BITalino and OpenBCI in education provides an accessible gateway to practical biosignal learning. BITalino is particularly valuable for its focus on education and its low cost, making it ideal for introducing students to

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Accuracy: 0.9
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.90      0.90        62
           1       0.90      0.90      0.90        58

    accuracy                           0.90       120
   macro avg       0.90      0.90      0.90       120
weighted avg       0.90      0.90      0.90       120
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Fig. 7. Report of the classfication

biosignal acquisition and analysis without significant investment [30]. On the other hand, projects should be compared with a gold standard for validation, or alternatively, have a first approximation if the model is close to being real and plausible. In this sense, there are studies that support the use of BITalino as a tool that can provide confidence in yielding results close to a gold standard. In a study conducted by Diana Batista in 2019, she compared the use of the BITalino kit and the clinically used system called BioPac, demonstrating that for her tests, the values obtained were very close [28].

In the laboratory practice using the BITalino Kit, students completed an exercise involving the collection of data from the quadriceps muscles. They were able to follow the entire process from acquisition to classification, demonstrating the kit's effectiveness in practical biosignal learning. This was enhanced by the strategy used in the classes, which was based on the flipped classroom methodology, as there is evidence that using this approach enhances the development of classes, especially when there is a lot of content to cover [29]. Despite these positive results, the study has limitations, mainly related to the sample size and participant diversity, which could affect the generalization of the results. Additionally, the exercise design focused on specific muscle movements under controlled conditions, limiting its applicability in real-world scenarios. Future research should explore a wider variety of movements and environments to enhance the relevance and applicability of the study.

Significant values were obtained in the extraction of features such as root mean square (RMS), mean, standard deviation, and amplitude from each time window (8 seconds). The developed random forest machine learning model showed a 90% accuracy, indicating suitable performance for the given data. These results highlight the effectiveness of the feature extraction process and the robustness of the machine learning model in accurately classifying muscle fatigue.

Following the aforementioned points, it is concluded that a machine learning model has been successfully developed to determine the muscle fatigue threshold through the analysis of electromyographic signals in the lower limb of a non-athlete population, using an incremental power test performed on a stationary bike. This model can be integrated into a microcontroller, achieving a more streamlined and ergonomic design. The successful development of this model opens up possibilities for its application in various fields, including sports science, rehabilitation, and ergonomics, where the ability to accurately detect muscle fatigue can lead to improved performance and reduced risk of injury. It show the potential of developing prototipies of technologies in classroom [31].

VI. Future works

Evaluating the outcomes resulting from the implemented educational strategy is essential to validate the effectiveness of our pedagogical approach and its impact on student learning. For future works, we propose the integration of both quantitative and qualitative assessment methods that allow for measuring the acquired knowledge as well as student satisfaction and perception regarding the flipped classroom model and the use of the BITalino kit. These evaluations would include pre- and post-activity tests to assess knowledge gain, as well as surveys and focus groups that will explore the students' experiences and opinions on the methodology and tools used.

VII. Conclusion

- The integration of new technologies in higher education, such as the flipped classroom model and the BITalino kit, provides better learning opportunities for engineering students, especially in the field of biomedical engineering.
- The flipped classroom model, which allows students to access pedagogical material before classes, has proven effective in increasing motivation and learning in engineering.
- The BITalino kit, with its portability and adaptability, is a valuable tool for education and research in bioengineering, allowing for hands-on experiences with biosignal acquisition and analysis.
- Using technologies like the BITalino kit in the classroom allows students to work directly with biomedical signals, such as EMG, improving their understanding of signal acquisition, filtering, and processing.
- These technologies not only offer a cost-effective entry point for students to learn about biosignals but also prepare them for the technical challenges of the field.
- By incorporating technologies like the BITalino kit into higher education, educators can create immersive learning experiences that equip students with the skills and knowledge needed for the evolving demands of the industry.

VIII. Disclaimer

The data collected for this project was conducted as part of the ISB course sessions. Students participating in the course formed groups for the dynamics and provided consent for the publication of the results obtained from the data. This approach ensured that the data collection process was aligned with the educational objectives of the course, allowing students to engage actively in the project.

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