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Special Issue
Detection and Modelling of Biosignals

Edited by
Dr. Sami Azam, Dr. Zubaer Ibna Mannan and Dr. Kawsar Ahmad

MDPI

https://doi.org/10.3390/info16030162

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A Graduate Level Personalized Learning Environment in the Field of f-NIRS Signal Processing

Dominique Persano Adorno [1,*] and Giuseppe Costantino Giaconia [2]

[1] Department of Physics and Chemistry, University of Palermo, Viale delle Scienze, Ed.18, 90128 Palermo, Italy
[2] Department of Engineering, University of Palermo, Viale delle Scienze, Ed.9, 90128 Palermo, Italy
* Correspondence: dominique.persanoadorno@unipa.it

Abstract: Active student involvement and instruction through experience in everyday contexts are pedagogical approaches suitable to promote inquiry-based learning and improve learners' cognitive skills. Nevertheless, many university and postgraduate courses offer lecture-based instructions of theoretical concepts to the students; little attention is still devoted to design hands-on activities, to improve practical/technical competencies and enhance students' effective understanding of the concepts. The development of a personalized, student-centered learning environment that encourages teamwork and inquiry-based learning aligns with the contemporary push for interdisciplinary education in bioengineering fields. This is particularly relevant for fostering expertise in emerging technologies like functional Near-Infrared Spectroscopy (f-NIRS). In this framework, this paper reports a lab activity for bioelectronic engineering and/or biomedical science students focused on analyzing prefrontal cortex activation during a memory task, processing the f-NIRS signals. This pilot activity, conducted at the University of Palermo (Italy), involved Master's and Ph.D. students working in teams to address challenges in experimental design. The study combines cutting-edge biosignal detection techniques with innovative educational strategies, offering substantial contributions to both bioengineering and educational research. The outcomes suggest that a hands-on and student-centered laboratory, experienced through a methodical sequence of self-directed learning activities, could considerably boost the student motivation to learn and the level of engagement in bioengineering and biosciences.

Keywords: innovative educational environment design; f-NIRS technique; biosignal detection and analysis; impact analysis

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Academic Editor: Francesco Beritelli

Received: 11 December 2024
Revised: 17 January 2025
Accepted: 17 February 2025
Published: 21 February 2025

Citation: Persano Adorno, D.; Giaconia, G.C. A Graduate Level Personalized Learning Environment in the Field of f-NIRS Signal Processing. *Information* **2025**, *16*, 162. https://doi.org/10.3390/info16030162

1. Introduction

Recent trends in education emphasize the need for a progressive switch toward a student-centered teaching approach, where learners actively take part in the learning process [1,2]. This strategy is based on the understanding that knowledge is gained by students through active learning rather than by being directly transmitted by the instructor [3]. Challenge-based, discovery-based, or inquiry-based teaching approaches, which endorse an engagement in activities like those performed by researchers, foster self-directed learning activities, enhance students' involvement, and provide the students with chances to strengthen their comprehension on how scientific knowledge is generated in real research frameworks [4–12]. Practice could help with theoretical understanding if there is a high level of integration between lectures and training [13,14]. Real-world educational environments make learning a meaningful personal experience, which increases students' motivation to learn [15]. Consequently, university curricula should include internships, collaborative learning, and integrative laboratory experiences appropriate to raise investigations capabilities, significance, and hands-on practice [16].

During the last decades, several studies focused on strategies to improve teaching and training in biosciences/bioengineering courses, but efforts have mainly concentrated on what and how to teach and on methods of recruiting undergraduate students [17–19]. On the other hand, biosciences/bioengineering students are required to be trained in real healthcare sites. At the Fourth BME Education Summit (held at Case Western Reserve University in Cleveland, Ohio in May 2019), organized by the Council of Chairs of Bioengineering and Biomedical Engineering, the Learning Environments tracks were discussed in six interactive workshops that provided discussion and recommendations in the areas of: (1) authentic project/problem identification in clinical, industrial, and global settings; (2) experiential problem/project-based learning within courses; (3) experiential learning in co-curricular learning settings; (4) team-based learning; (5) teaching to reach a diverse classroom; and (6) innovative platforms and pedagogy [20].

In this context, Singh et al. have developed a series of bioengineering courses with active and experiential components within an interdisciplinary learning environment [21,22]. In the first course, Biomechanics, learners were immersed in a simulated laboratory environment that included manikins normally used for teaching in the Nursing School. Each group identified possible technological challenges directly related to the manikins' biomechanics and debated an improvement to overtake the challenge. In the second course (Medical Devices), engineering undergraduates worked in teams with nursing students within real-world clinical contexts and simulation scenarios. Their task was to detect three unmet needs in real-world clinical settings and propose a feasible solution. This methodology helped learners to understand and use real-world applications of engineering principles in solving problems. Altogether, the inclusion of clinical immersion in interdisciplinary teams enabled the integration of active and experiential learning, while giving engineering undergraduates greater awareness of their profession, adaptive skills, and an understanding of the roles and responsibilities of other specialists involved in improving patient safety and well-being [21,22]. Berry et al. described the features of a digital tool used in an inter-professional activity aimed to increase collaborations among clinicians and STEM undergraduates or graduates [23]. The open access instrument has provided doctors and STEM students with a channel for efficient team building around unsolved clinical problems, granting a continuous exchange of ideas among participants through several clinical subjects.

Montesinos et al. leveraged blended learning environments to create innovative educational experiences within a biomedical signals and systems analysis course in the Bachelor of Science in Biomedical Engineering program. The goal was to enhance students' motivation, interest, and the perceived relevance of the material [24]. They designed a learning experience centered on wearable devices and cloud-based collaborative development platforms, enabling students to transform everyday scenarios into experiential learning opportunities. Their findings indicate a positive impact on students' perceptions of the learning experience, particularly in terms of relevance, motivation, and engagement [24]. In higher education, wearable technologies have been recognized as transformative tools for teaching practices due to their potential to enhance learning experiences [25,26]. These devices promote student interaction, foster engagement, and facilitate active learning methodologies. Recently, the same group at Tecnológico de Monterrey successfully implemented a Challenge-Based Learning (CBL) experience in an undergraduate biomedical instrumentation course, delivered in a blended format with remote lectures and in-person laboratory sessions [10]. During the in-person CBL activities, students were tasked with designing, prototyping, and testing a respiratory or cardiac gating device for radiotherapy.

Collaboration with an industry training partner was instrumental, as it provided students with a highly engaging and challenging opportunity to acquire new knowledge and skills while solving a real-world, industry-relevant problem [10]. A similar initiative was introduced at the University of Palermo, where a laboratory workshop offered engineering students an open inquiry-based, hands-on learning experience [11]. Students were required to design, develop, and test a prototype of an augmented protective mask equipped with embedded sensors for monitoring basic health parameters. All stages of the lab activities were documented, emphasizing the students' perspective on addressing and solving a real-world scientific problem. Although limited to a case study, the results highlighted the effectiveness of an educational framework focused on contextualized, student-centered laboratory activities, which foster motivation, transferable skills, and improved learning outcomes [11].

Emily Farrar discussed the design and implementation of a four-week Design Thinking CBL initiative in a biomedical instrumentation course, aimed at bridging the gap between education and industry. She also examined the project's impact on students' perceptions of their learning outcomes and readiness for postgraduate endeavors [27]. The project involved ten students, four doctoral candidates, and six individuals employed in the engineering industry. To evaluate students' perceptions of their learning and postgraduate preparedness, the "Student Assessment of Learning Gains" instrument and a postgraduate survey were utilized. The findings revealed a positive impact on students' readiness for both industry roles and advanced academic studies [27]. The Design Thinking framework of the project, combined with its implementation in a flexible classroom setting, further facilitated the integration of formative feedback from the instructor and peers. This feedback mechanism significantly enriched students' engagement with disciplinary practices.

A group of undergraduates in Bioelectronic Engineering at the Department of Engineering of the University of Palermo was actively engaged in a laboratory workshop about a real-world applied biosciences issue—the classification of digital ophthalmologic signals [28]. The participants in the lab activity had the task of discriminating eye signals belonging to healthy subjects from those belonging to patients affected by one of two typical retinal pathologies: Congenital Stationary Night Blindness (CSNB) and Achromatopsia (ACR). Students used software based on both the Empirical Mode Decomposition and an Artificial Neural Network for processing and classifying the electroretinograms [29]. Investigations on the effectiveness of this specific implementation showed that participation in this activity, based on an inquiry-led learning methodology, provided a significant contribution to undergraduate outcomes, also producing positive effects on the students' learning aptitude [28].

Education and training should be dedicated to fulfilling the constant needs of skilled scientists on biomedical signals processing [30], integrating technical advances of signal analysis into the educational environment while sharing proposed approaches with a broad community [31]. The signal processing and identification methods, normally used in physics contexts, could be able to reveal hidden peculiarities in biomedical signals, gaining an increasing importance in various diagnostic fields and obtaining more reliable results in the clinical field [32–35]. However, noise reduction and signals analysis involve several boring concepts that keep an intrinsic physical meaning, frequently hard for students to understand. Consequently, learners could easily get bored in a theoretical teaching environment. Therefore, it is necessary to use experimental teaching approaches to help students to discover the connection between theoretical computations and real phenomena, with the goal of not only strengthening classroom knowledge but also of encouraging students' independence and enhance students' interest [10–12]. Recent studies have emphasized the importance of integrating practical, technology-driven approaches into biosignal education, underscoring the impact of hands-on activities and practical frameworks in biosignal interpretation. These approaches have included novel techniques for biosignal detection and processing, which significantly contribute to the integration of emerging technologies in the curriculum [36–40]. This paper builds on these findings, showcasing how such frameworks can be applied effectively in a graduate level context. Indeed, despite the fact that undergraduate biomedical and biosciences activities are rapidly increasing, to the best of our knowledge, there are few papers devoted to innovative approaches for engaging graduate and/or postgraduate populations. Shortages of textbooks and laboratory activities make it difficult to effectively teach biosciences and biomedical engineering at the graduate and postgraduate levels. By bridging the gap between theoretical instruction and practical application, this paper provides a pedagogical approach and valuable insights into the design of innovative educational models in biosignal processing for Ph.D. or Master's level students—who often do not have the opportunity for such laboratory experiences.

The proposed educational pilot builds on recent research findings, focusing on personalized, graduate level educational activities in functional Near-Infrared Spectroscopy (f-NIRS) signal analysis, thereby contributing to biosignal detection and modeling advancements. The purpose of this learning setting is to add to the traditional classroom lectures a research-based lab experience about the acquired theoretical principles, establishing a connection between the textbook notions and their usage in the laboratory. The proposed learning experience includes the use of practical expertise and procedures barely available in textbooks, offering hands-on activities aimed at exploring biosciences phenomena by managing real data for scientific evaluation and explanation. Given that students' exposure to active learning-based laboratory experiences could be effective in acquiring knowledge, the learning path discussed should: strengthen students' comprehension and retention of the theoretical matter; develop investigative and critical thinking competencies; boost communication and teamwork skills among students; and, finally, achieve learners' satisfaction.

The paper is organized as follows: in Section 2, we describe the materials and methods of our study; in Section 3, we describe the background principles of f-NIRS and introduce f-NIRS signal filtering and processing. In Section 4, we provide details of the learning project steps and describe the results of the pilot study. Sections 5 and 6 discuss an evaluation of the laboratory experience, using feedback from participants together with directions and recommendations for future developments. The conclusions are reported in Section 7.

2. Materials and Methods

In the last decades, numerous research studies have focused on investigations of the cerebral cortex functional processes with the aim of identifying the sources of disorders associated with the neurological compartments and of correlating them with the brain tissues' functional processes. The interaction among synapses, neural cells, and interconnected brain areas constitutes the core of very complex mental processes. Both the investigations of brain tissue mechanisms during cerebral events and the evaluation of the bio-processes affecting information understanding and memorization play key roles in cognitive neuroscience. Measurement of cerebral oxygenation and the study of hemodynamics are crucial in modern medical diagnostics.

Functional Near-Infrared Spectroscopy (f-NIRS) is an advanced and non-invasive method for the functional observation of cerebral cortex hemodynamic activities, largely used for the examination of post-traumatic pathologies, for cognitive neuroscience, and for probing depression, schizophrenia, and other psychiatric disorders [41–45]. Contrarily to electroencephalography (EEG) and magnetoencephalography (MEG), which represent a direct measure of the electric or magnetic field vectors produced by the neurons activity, f-NIRS monitors variations in oxyhemoglobin (HbO_2) and deoxyhemoglobin (HHb) concentration associated with the neuronal activity. When the subject performs a particular task, neurons of the associated brain compartment modify their metabolic needs, producing a change in the concentration of oxygenated hemoglobin. The f-NIRS method explores the absorption response of some bodily fluids elements to electromagnetic radiation in the spectral range between 650 and 950 nm by measuring the amount of diffused light passing through the brain cortex.

The laboratory activity presented here is dedicated to the acquisition and analysis of real f-NIRS signals by using a pioneering instrumentation located at the Digital Programmable Electronics Systems Laboratory (ESDP-LAB) of the Palermo University and developed within the framework of a European research project. The project aimed to provide advanced imaging and detecting technologies for monitoring, diagnosing, and therapeutic applications, making it possible to observe physical conditions for any subject regardless of clinical status and age [46]. One of the ultimate goals of the project was to develop optical devices that, by making optimal use of the spectral imaging properties of near-infrared light, made available less invasive, smaller, lower-cost, more reliable, and easier-to-use systems [46].

The extra-curricular activity was structured in a series of afternoon meetings lasting a total of 24 h, arranged in the fulfillment of different phases. Table 1 includes a description of the different phases of the course, the hardware and software needed, the extent of each phase, and the learning outcomes; Figure 1 is a picture of the system deployment with students.

With the aim of investigating the feasibility of the proposed learning path, three graduates in the Electronic Engineering Master's program and one student during his Master's Thesis work were involved in this educational pilot at the ESDP-LAB. Before the reported study, the four participants had no experience of biomedical signal processing at all. However, all of them, during their second year of the Bachelor's degree, had followed the basic course of Signal Theory, focused on the processing of electronic signals (but not of biosignals).

Table 1. Description of the different phases of the course.

Phase of the Workshop	Hardware and Software Needed	Duration (Hours)	Learning Outcomes
Introduction to physics and physiological concepts at the basis of the f-NIRS technique (traditional lecture)	Textbooks and Scientific Literature	3	Understanding of the basic concepts related to the f-NIRS technique
Choice of the experimental acquisition paradigm and its implementation	Homer2, Matlab	6	Understanding of specific biomedical Software and bio-parameters related to Beer–Lambert Models
Test measurements collection	f-NIRS Hardware prototype	3	Understanding of experimental test variations and measurements Tolerance of biosignals
Analysis of the f-NIRS signal characteristics, filtering, and processing	Homer2, Matlab	12	Understanding that noise removal from f-NIRS signals represents one of the most compelling research objects in the field of biosignal processing. Understanding how to extract appropriate features to characterize the f-NIRS biosignal

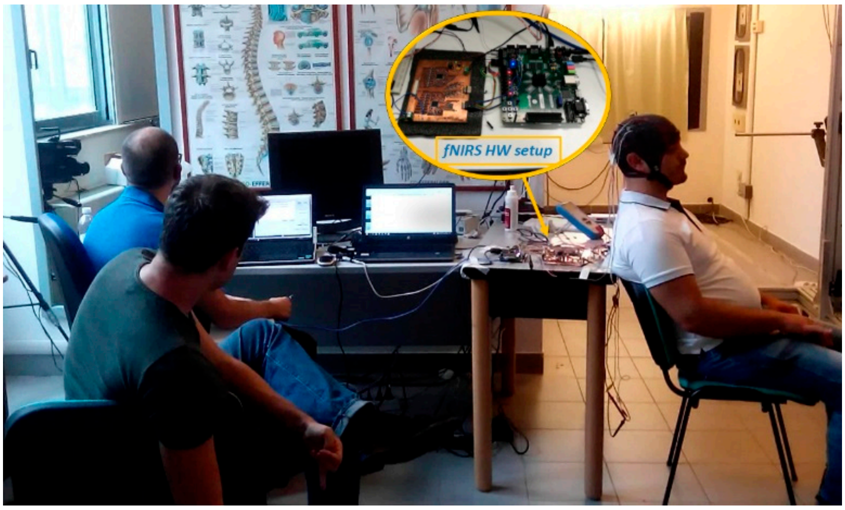

Figure 1. Image of the system deployment.

A pilot study is the small-scale training that aids in the design and modification of the main study; it is generally carried out on a few members of a target population and represents the preliminary investigations necessary to avoid an inadequately designed teaching–learning project and to obtain high quality educational results. Moreover, in educational settings, a pilot study offers a potentially valuable insight to improve the chances of a clear outcome, to evaluate feasibility, duration, and difficulties, and to improve upon the learning environment design prior to the performance of a large-scale study.

The Experimental Lab Prototype Set-Up

The ESDP-LAB experimental set-up utilizes dual wavelength LEDs which inject infrared light into the scalp and recover the partially diffused and partially scattered light from the same surface—but a few centimeters away from the optical source [47]. Several source–detector pairs (called f-NIRS channels) ensure spatial resolution over the entire head, providing a complete map of cerebral oxygenation. Since the human scalp has rather considerable attenuation values in the infrared region, the detecting system has been realized through very sensitive detectors, reaching a counting capacity of a single photon [47,48]. Silicon photomultipliers (SiPM) and dual wavelength LED sources (735 nm and 850 nm) were fixed on a standard EEG cap, manufactured by g.tec Medical Engineering (see Figure 2). The cap has multiple holes through which sources and detectors are anchored; in correspondence with each one of them, the alphanumeric reference, according to the 10–20 international standard used in the EEG domain, is reported to facilitate the identification of the channels to be considered for acquisition. In the pilot study, two source–detector pairs were used. The source and the detector belonging to the same channel were 3 cm apart from each other. Channel A, consisting of the source–detector couple S1–D1, affected the prefrontal cortex area of the right lobe; channel B, consisting of the source–detector pair S2–D2, affected that of the left lobe. Both sources were equally spaced from the inter-hemispherical line. Cortical areas involved belong to the anatomical segment called the polar frontal cortex (PFC).

Hardware details of the developed system are outside the scope of this work and can be found in [47–49], while commercial systems capable of providing a similar dataset to the market with a range of different performances are available. BioPac, Artinis, and NIRx are a few examples of companies producing relatively small f-NIRS systems suitable for R&D purposes, while ISS, Hitachi, and others are devoted to producing heavy and very expensive systems featuring a higher number of optical channels.

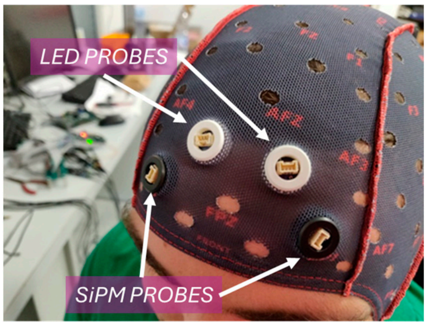

Figure 2. Cap produced by g.tec Medical Engineering (http://www.gtec.at/, accessed on 16 February 2025) arranged with LEDs and SiPMs sensors.

3. The Background Principles of f-NIRS

The variation in hemoglobin concentrations is determined through an empirical relationship, the "modified" Beer–Lambert law (MBLL), which relates the quantity of incident light absorbed by a medium of a certain chemical nature with the hemoglobin concentration and the tissue thickness [50–52]:

$$I = I_0 e^{-\mu_a \times PPL \times sd} + g \tag{1}$$

where I is the detected light intensity; I_0 is the intensity of the incident light; PPL is a parameter that accounts for increasing of photon path length due to multiple light scatterings in tissue; sd is the source–detector distance; μ_a is the coefficient of optical absorption; and g is a suitable factor accounting for the measurement geometry [51]. Otherwise, the MBLL is given by:

$$OD = -log \frac{I}{I_0} = \mu_a \times PPL \times sd + G \tag{2}$$

where OD is the optical density; log is a natural algorithm with base e; and G is an appropriate factor correlated to the measurement geometry. The total average path-length of revealed photons is $L = PPL \times sd$ [51].

Because of the high number of interactions of the e.m. waves in heterogeneous biological tissues, a large number of pathways of the emitted NIR light is possible. Because scattering is a random phenomenon, it is very difficult to estimate a trajectory that considers the inhomogeneity of the medium and the varied nature of the crossed tissues. In order to define a probable scattering trajectory, it is possible to simplify the problem by hypothesizing a discrete homogeneity of the tissues, as in the "Banana" model, which attributes a constant probability of being traversed to the regions crossed by the photons emitted by the sources. In this model, the probability distribution has a banana shape, where the regions most likely to be crossed are the deeper central ones [51,53,54]. Consequently, the distance reached by the photons emitted by the sources is proportional to the space between the source and the detector.

f-NIRS Signal Filtering and Processing

In the time interval following the onset of a stimulus, the equilibrium between HbO_2 and HHb should follow a characteristic trend as a function of time known as the Hemodynamic Response Function—HRF. Nevertheless, depending on the nature of the stimulation and the brain region associated with it, several factors may affect the curve shape. Functional neuroimaging research aims to quantitatively establish the structure and the specific characteristics (onset, latency, amplitude, etc.) of the HRF.

The hemodynamic response function includes several spurious contributions due to physiological oscillations and noise components related to the measurement conditions. The most important noise source is composed of the physiological signals, significant both at the surface level of the scalp and at the underlying cerebral cortex. The main physiological signals are (i) the heartbeat (frequency range 0.8–2.0 Hz), (ii) respiration (frequency range 0.1–0.3 Hz), and (iii) the Mayer wave (frequency range 0.04–0.15 Hz) and the very low frequency oscillations (about 0.004 Hz). These components have distinct frequencies and amplitudes but overlap with the hemodynamic response, affecting the processing of the f-NIRS signals and extensively influencing the estimation of oxyhemoglobin and deoxyhemoglobin concentrations. Furthermore, electronic components represent a noise source at high frequency. For these reasons, it is necessary to adopt suitable filtering actions on a signal band where useful information resides and to consider the frequency variability of the hemodynamic response related to specific tasks such as motor or cognitive [55]. The most frequently used investigations method in time series processing is the Fourier spectral analysis, mainly due to the simplicity and efficiency of the Fourier transform. However, optimal use of the Fourier analysis requires strictly periodic or stationary data so that the signal can be decomposed as a sum of sinusoids. This is not the case with biosignals, such as f-NIRS waveforms, which are almost always non-stationary.

There is still no recognized method to correctly estimate the hemodynamic response from the f-NIRS signal, and each used methodology has some advantages and limitations.

4. The Graduate Level Educational Pilot

In the following, we describe the characteristics of our educational pilot project, considering the involved topics and the results, the difficulties reported by the participants attending the ESDP Laboratory, and how they faced and overcame them; we also suggest viable solutions for optimizing the laboratory experience.

4.1. Choice of the Experimental Acquisition Paradigm and Its Implementation

The purpose of this phase of the educational project was the selection of the acquisition procedure, that is, the sequence of stimuli, whose order and extent represent the study protocol. Prior to selection, the students compared different acquisition paradigms for investigations of the prefrontal cortex activation through f-NIRS. These paradigms were proposed in the literature for any sort of stimulus: auditory, visual, visuospatial, etc. [56–63]. The student participants analyzed the benefits and limitations of the most used protocols and agreed to look at the impacts of memory workloads, as these usually produce the brain's hemodynamic reactions [61–66]. The students exploited an n-back task [64–66] to generate various levels of memory workload, asking the study subjects to recall the last one, two, or three of quickly varying digits. Six healthy subjects (2F, 4M; 29 $\pm$ 5 years old) were involved in performing this specific Working Memory Load (WML). The measurements here reported, performed according to the principles of the Declaration of Helsinki, were carried out on laboratory colleagues and students, properly instructed on the non-invasive procedure. The students made five acquisitions at different workload levels (1-, 2- and 3-back WML) for each test subject, with a total of 15 acquisitions per subject. Each trial consisted of two 30 s periods of relaxation interspersed with a 45 s phase in which the test subject carried out the requested activity in response to the visuospatial stimulus displayed on a PC monitor. The used visuospatial stimulation (see Figure 3) consisted of a 3 $\times$ 3 grid, where the squares are randomly red colored during the test. Each square remains on, and then off for 1500 ms, for a total latency time of 3000 ms. The n-back task requires a positive response from the subject when the same-colored square is visualized after n steps. Every single acquisition lasted 105 s, and the software package latterly processed the number of correct answers reporting the success percentage.

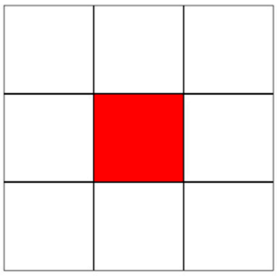

Figure 3. Grid used in this study for visuospatial stimulation.

The student participants in our workshop utilized the Homer2 software (version 2.8) package for setting up experimental constraints, as well as registering the head geometry, arranging the probe, and setting the wavelength [67,68]. Homer2, developed by a group of researchers at Harvard University, is an open source software commonly used in f-NIRS studies; it supports numerous MATLAB R2016a (9.0.1) (The MathWorks®, Inc., Natick, MA, USA) functions and a reasonably user-friendly graphical user interface (GUI) for uploading, visualizing, managing, and evaluating f-NIRS waveforms. By means of this software, the experimental data, expressed in terms of voltage proportional to the detected light intensity, are converted into optical density (absorbance) and latterly into oxy- and deoxy-hemoglobin concentrations.

4.2. Choice of f-NIRS Signal Filtering and Processing

Participants in the educational pilot decided to use a low-pass filter with a cut-off frequency of 0.4 Hz in order to mitigate any biological effects. However, this filtering did not completely remove the underlying physiological noise associated with the Mayer component and the breath frequency.

The participants computed brain oxygenation by analyzing signal changes with respect to the baseline. A visual inspection of each raw data series was promptly carried out to discover possible movement artefacts, easily distinguishable as signal peaks. In fact, although the subjects under testing had closely observed the protocol, some acquisitions featured movement artefacts during the relaxation phase (first 30 s); for this reason, these acquisitions were removed before subsequent processing phases. Some peaks related to the cognitive tasks were also present in the acquired data, especially during the first ten seconds from the start of the task. Since there is no agreement in the literature on the existence of a delay in activating concentrations with respect to the beginning of the task, our pilot participants preferred not to eliminate those trials from the subsequent analyses. After this skimming step, the data were processed by using the Homer2 software interface, computing oxygenated and non-oxygenated hemoglobin changes for each optical channel.

The student participants estimated the average values acquired by each channel and each acquisition during the first 30 s of relaxation, using it as a baseline for the rest of the acquisition related to the different tasks. Each raw dataset was then normalized with respect to the baseline level. Moreover, the average values of signal variations over the five different acquisitions associated with a particular cognitive task were carried out on each channel and subject basis. The participants decided to use this procedure to evaluate the possible existence of a change in HbO_2 and HHb levels while increasing the cognitive load. Furthermore, they found this procedure to be useful for qualitatively evaluating the sensitivity of the experimental set-up. These preprocessed temporal waveforms were then statistically analyzed searching for possible correlations between cognitive load and hemodynamic response, with the final goal of extrapolating features suitable for characterizing the f-NIRS signal of healthy subjects.

In Figure 4, we show, as an example, HbO_2 changes detected by channels A (upper panel) and B (bottom panel), respectively, during the 1-back task period. Each panel highlights a continuous black line with the average of the six subjects. However, it was observed that this analysis did not provide the possibility of extracting appropriate features in order to characterize the f-NIRS signal of healthy subjects as a considerable curves' variability, either in terms of values or trends.

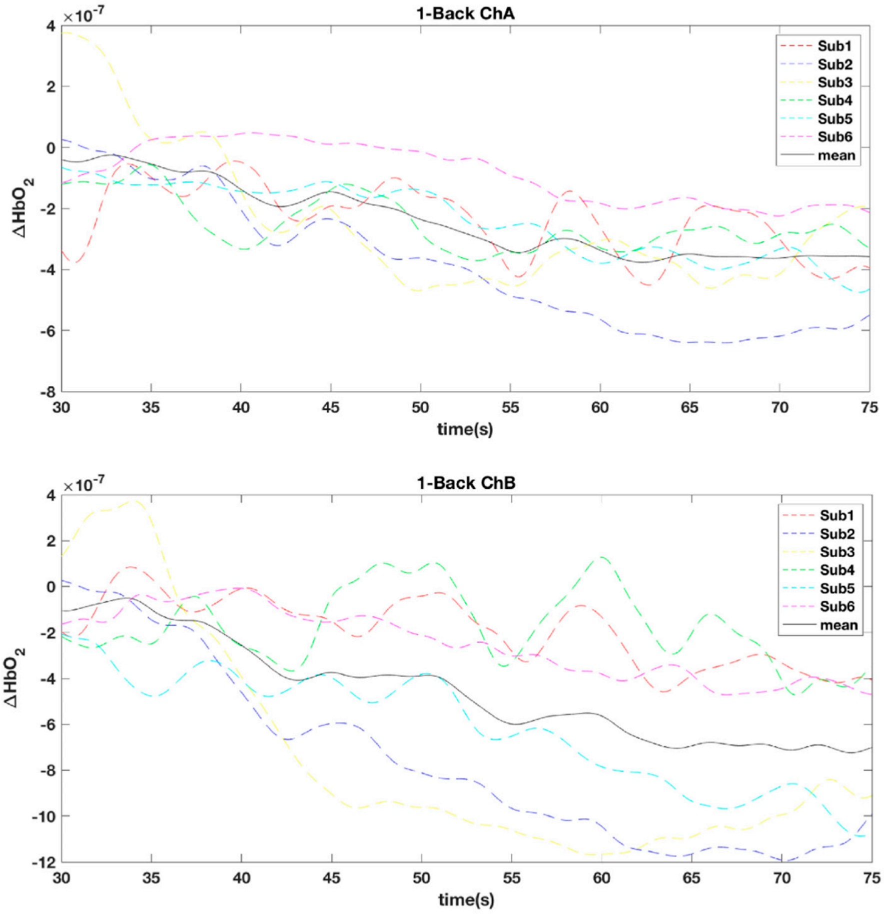

Figure 4. Changes of HbO_2 during the 1-back task detected by channel A (**upper panel**) and channel B (**bottom panel**), respectively.

With the aim to achieve more accurate information on peculiar latency time and frequency, the f-NIRS waveforms were processed by means of the Continuous Wavelet Transform (CWT), investigating on the signal spectrum evolution over time. The scalogram, obtained by the CWT, permits detection of the time–frequency location of both the hemodynamic response and the noise components corresponding to suitably selected time windows. As an example, by observing the panels of Figure 5, it is possible to compare the scalogram obtained during the relaxation phase (left) with the one corresponding to the 1-back cognitive workload (right). The scalograms refer to the whole unfiltered acquisition of one of the test subjects (subject 4). In both panels, the physiological noise due to the heartbeat (about 1.2 Hz) and noise contributions at a higher frequency are detectable. However, in the right panel, it is possible to see the appearance of frequency components placed after the first 30 s, which could be related to the cognitive workload, while contributions—located in the 0.2–0.3 Hz window—may account for the respiratory and the Mayer components.

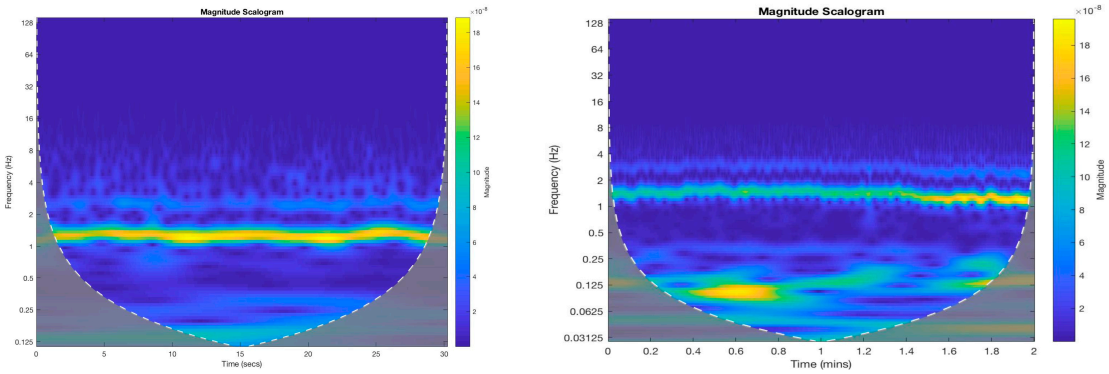

Figure 5. CWT scalograms over a whole unfiltered waveform: (**left**) during the relaxation time; (**right**) during the 1-back cognitive load.

The panels of Figure 6 show the scalograms related to the relaxation time and the 45 s of the task obtained after signal filtering. During the relaxation period, the scalogram showed relatively low-amplitude visible noise components. In the time interval of activity (1-, 2- or 3-back), it was possible to detect intense components, mainly located in the 0.1–0.2 Hz range, which could be used as a feature that characterizes the healthy subject response in order to classify the different cognitive load levels.

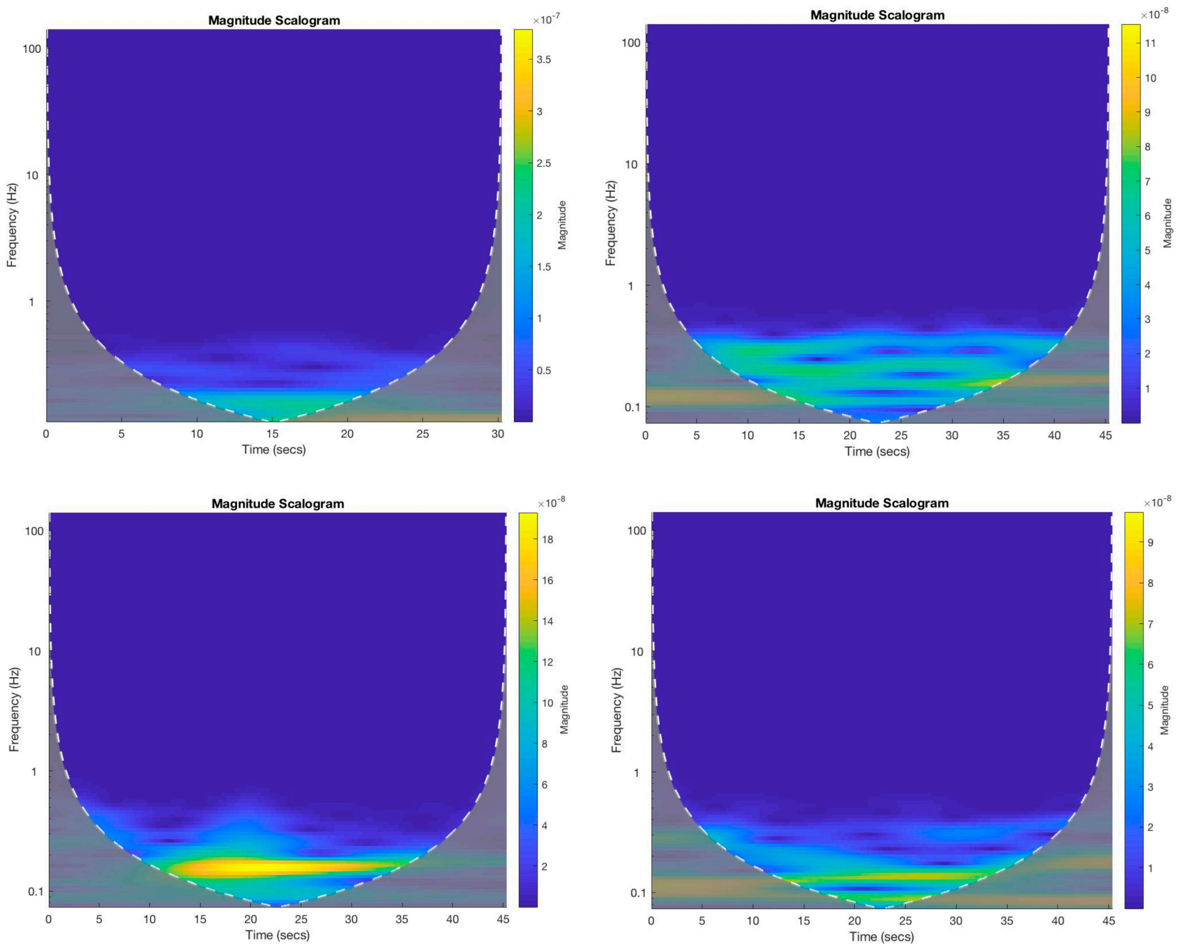

Figure 6. Scalograms obtained by applying the CWT after the filtering of the signal over: (**upper left panel**)—the relaxation time (30 s); (**upper right panel**)—the 1-back task period (45 s); (**bottom left panel**)—the 2-back task period (45 s); and (**bottom right panel**)—the 3-back task period (45 s).

As it occurs in investigations of other biosignals, these features could be used for the implementation of adequate classifiers or to train a neural network.

5. The Feedback from the Participants in the Pilot Educational Project

After completing all the lab activities, we collected the participant feedback about this educational workshop. With the aim of highlighting the "lights and shadows" of the proposed learning environment, we administered a questionnaire to the four participants and analyzed their answers.

The questionnaire consisted of six specific items adapted to this specific study from the Intrinsic Motivation Inventory (IMI) [69]. The analysis is here limited to three subscales: (i) the contextualization/perceived competence; (ii) the interest/satisfaction; and (iii) the required effort/frustration. A 5-point Likert scale was used to record responses to these questions, with 1 representing strong disagreement and 5 representing strong agreement, reflecting the degree to which the students agreed with the collection of items. Of course, due to the small number of participants to this pilot experience, the analysis of the answers to the survey needs to be continued until the number permits a full statistical validation of the data. However, it is still worthwhile to provide a general overview of the participants' point of view; it is with this aim that we report, in Table 2, the questions and the average score of each item of the survey.

Table 2. The six questions used in the survey. Based on a 5-point Likert scale, the average outcome for each item is listed.

Please Tell Us to What Extent You Agree with the Following Statements	Average Score of Participant Answers
Contextualization/Perceived competence	
(Q1) The analysis of f-NIRS signals is a good way to introduce the methods of processing non-stationary signals (learning by doing)	4.5
(Q2) After this lab workshop, I became rather skilled on biosignal processing, and I feel more competent	4.75
Interest/Satisfaction	
(Q3) Attending this lab activity was very interesting	4.75
(Q4) I'm very satisfied with the learning experience in general	5
Effort	
(Q5) I put much effort in performing this activity	4.25
(Q6) I will recommend this workshop to Master's or Ph.D. students in Applied Sciences or Engineering	5

The first two questions in the survey could be considered qualitative feedback about the importance of the contextualization of research (Q1) and the awareness of the acquired knowledge (Q2). The four questions (Q3–Q6) do not directly relate to learning outcomes but rather to the overall vision of the learning experience: the high scores from all the participants indicate that the proposed laboratory experience has been enjoyable and successful, under the point of view of interest, satisfaction, and motivational aspects. Participation in this educational environment gave the learners the chance to make use of previously gained notions in understanding the purpose of the CWT to solve real problems.

By observing the way issues about the f-NIRS biosignal scientific investigations were faced by the participants, we have noticed continuous educational growth and a great level of engagement which could be considered a qualitative measure of the impact, in terms of learning benefits, of this educational experience. Furthermore, in structured interviews performed at the end of the laboratory sessions, the participants attending this pilot study claimed great knowledge and competence improvement on processing biosignals, critical thinking, and scientific investigations skills. The knowledge gain, as a result of the participation to this lab workshop, needed more effort than merely a formal phase of content transmission. However, although the activity was very demanding (Q5), it did not generate frustration or a loss of interest in the participants: all of them will recommend attendance to this lab workshop to their Master's degree or Ph.D. colleagues in Applied Sciences or Engineering in order to enhance deep learning, inquiry-based research skills, and technology/lab practice (Q6).

6. Indications and Recommendations for Future Developments

In this learning workshop, the students—acting as scientists—had to: (i) learn the physical basis of wave–matter interaction of complex phenomena, creating their own inquiries, discussing with peers, and building a model; (ii) learn the use of f-NIRS instrumentation; (iii) choose and design the experimental paradigm for measuring the cerebral cortex activation; (iv) carry out the f-NIRS measurements; (v) deal with the processing and characterization of the acquired signals; and, finally, (vi) provide coherent explanations and draw their conclusions. In the following, we report on the main problems faced during the educational pilot by our participants and their suggestions for improving the learning environment. To deeply understand the background principles of f-NIRS, the learners should have a background knowledge on suitable physics thematics. Moreover, in order to use the experimental f-NIRS set-up with full awareness, an essential prerequisite is that the participants hold a Biosciences or Engineering bachelor. During the phases of the learning pilot, some participants experienced many difficulties using MATLAB® programming. Therefore, aiming to augment the effectiveness of the laboratory learning path, we recommended giving learners more program design experiences during their bachelor's courses, enabling them to fulfill the requirements of the proposed path [70]. MATLAB® notions could be acquired, for example, by using a flipped classroom teaching approach, in which engaged learners watch online video lectures and video tutorials and perform the homework needed [71]. Finally, the participants in the pilot study also asked the educators to introduce the statistical multivariate analysis approaches (such as the PCA-based pre-processing method) at the beginning of the learning activity. The participants in the educational pilot experienced some issues in designing and carrying out a significant sequence of scientific analyses by themselves, as open inquiry instruction requires. In these cases, the level of the instructor's guidance should be increased to avoid unnecessary frustration and stress. Accordingly, in order to obtain a more active level of student participation and greater satisfaction in learning, this lab experience could be transformed into an "elicited inquiry-based" learning activity, where educators may actively participate, acting as student "peers". This could result in more effectively promoting students' reasoning and critical thinking, stimulating their scientific inquiry as shown in Ref. [72].

As for the analysis of the f-NIRS time series, most of the problems highlighted by the participants in the pilot were related to the difficulties dealing with physiological signals affected by great variability. They tried to spot some of the key factors affecting this variability (the different head conformations among the six subjects, the incorrect positioning of the probes on the scalp, etc.) and made suggestions on how to improve the cap to ensure that a precise spatial position of the probes on the scalp could be reached. Furthermore, to minimize interference with the external environment, they recommended taking the measurements in a soundproof, almost dark room, in the absence of personnel not involved in the activity [73]. Our students also made suggestions on how to update the experimental paradigm. Since the limited number of trials did not allow for an accurate estimation of the hemodynamic response, to increase the statistics and thus improve the characterization of the signal, it would be appropriate to provide much longer cognitive tasks (at least 5 min). In this way, the signal can be divided into windows of different amplitude, making more time series available for unconventional analyses such as the wavelet transform or the empirical mode decomposition. Finally, to have the opportunity of studying possible effects of discrepancy between the responses of the two hemispheres, the learners suggested a greater number of channels for the acquisition process as well as the inclusion of a certain number of left-handed healthy subjects in the analysis.

7. Discussion and Conclusions

Learners gain a valuable education and hold long-lasting scientific understanding when they become capable of using it as a tool for advanced discovery. Efficient and effective science/engineering teaching should be general in nature, engage learners toward a deep knowledge of the important concepts, and train them to correlate cross-cutting phenomena that may at first appear unrelated. However, such as for any other educational activity, the pedagogical effectiveness of a learning setting largely depends on students' intrinsic motivation and interest.

This paper presents a hands-on, student-centered workshop designed for bioengineering and biomedical science students to enhance their understanding of functional Near-Infrared Spectroscopy (f-NIRS) signal processing. The activity focused on analyzing prefrontal cortex activation during a memory task, offering participants the opportunity to work collaboratively on real-world challenges related to experimental implementation and biosignal modeling. Conducted as a pilot study at the University of Palermo, the workshop demonstrated the potential of personalized, practice-based learning environments to significantly boost student engagement and motivation. The structured sequence of self-directed activities provided a robust framework for understanding biosignal acquisition and analysis, contributing to both technical skills development and cognitive learning strategies.

The proposed educational project allows us to introduce the biomedical signal processing theme to graduate and postgraduate Applied Sciences/Engineering students, highlighting the importance of the experimental paradigm, how to control the experimental set-up and gather the biosignals, and how to design a filter appropriate for reducing a specific noise component. It could help young scientists to strengthen the required abilities to overcome the unavoidable difficulties possibly encountered when facing a research challenge. Moreover, the logical sequence of the proposed laboratory activities might contribute to creating a more effective manner to employ theoretical knowledge in the research of solutions for real-world problems.

Although the number of students involved in this preliminary study is very low, we believe that its findings may be important for the Biosciences/Bioengineering Education community, mainly because of the lack of education studies dedicated to Master's or Ph.D. students. Of course, the representativeness and relevance of this pilot study do not reside in its statistical outcomes, but rather on the suitability of the study and on the experimental layout. Our findings could suggest that engaging students in constructivist active learning strategies lead to deeper conceptual comprehension, even of a complicated subject like that of f-NIRS signal interpretation. Providing concrete contextualization, the proposed laboratory activity could enhance both motivation and learning outcomes. By bridging the gap between theoretical instruction and practical application, this paper provides valuable insights into the design of innovative educational models in biosignal processing.

In our workshop, we adhered to approved ethical principles and emphasized the ethical responsibilities associated with f-NIRS signal processing and the use of personal health information. Our primary goal was to equip learners with the skills to handle sensitive data while upholding privacy and confidentiality. We underscored the importance of obtaining informed consent when collecting and processing biosignal data from human subjects. As science advances, the need to critically evaluate and communicate the broader implications of research becomes increasingly vital. Instilling a strong sense of ethical responsibility in learners is essential to fostering scientists who prioritize integrity and accountability.

To achieve this, various steps can be taken to educate students and team members about the ethical dimensions of neuroscience. This may include formal ethics training, discussions about the societal impacts of research, and the integration of ethics into the curriculum. Exploring regulatory frameworks and international ethical guidelines, such as the Declaration of Helsinki, can help ground students in global standards. Hands-on projects should incorporate reflections on the ethical aspects of the research process and its potential applications. Developing a strong sense of accountability fosters responsible practices in handling sensitive biological data and engaging with human subjects. Highlighting these efforts demonstrates a commitment to fostering not only scientific rigor but also ethical awareness. An ethically conscious generation of scientists is essential for advancing sustainable, equitable, and socially responsible innovation. Educators should also guide learners in examining the potential impacts of neuroscience work, both positive and negative. On the positive side, neuroscience advances can enhance our understanding of brain function, improve healthcare outcomes, and inspire innovation. Conversely, potential concerns include the misuse of technology (e.g., privacy violations or surveillance misuse), misinterpretation of findings, or unintended societal consequences. Engaging learners in discussions on how to address or mitigate these risks during the design and implementation of practical projects can further reinforce ethical mindfulness in their work.

We hope that this work, by underscoring the relevance of experiential approaches in biosignal detection and modeling education, could offer valuable insights into the design of innovative training programs that prepare students for challenges in bioengineering and applied biosciences. The analysis of the findings from this preliminary study encouraged us to plan some experimental studies with a larger number of students to validate the impact of the proposed approach, even considering the chance of extending this approach to the study of different biosignals.

Author Contributions: Conceptualization, D.P.A.; Methodology, D.P.A.; Software, G.C.G.; Validation, D.P.A.; Resources, G.C.G.; Data curation, D.P.A. and G.C.G.; Writing—original draft, D.P.A.; Writing—review & editing, D.P.A. and G.C.G.; Supervision, D.P.A. and G.C.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been partially funded by Ministero dell'Università e della Ricerca—Project 4FRAILTY, "Sensoristica intelligente, infrastrutture e modelli gestionali per la sicurezza di soggetti fragili" (Programma Operativo Nazionale "Ricerca e Innovazione" ARS01_00345). The study has also been conducted with the support of the Erasmus+ Programme of the European Union, grant number 2019-1-DE03-KA201-060125.

Institutional Review Board Statement: All procedures performed in this study were in accordance with the Declaration of Helsinki and its later amendments. The measurement protocol for the instrumentation developed at the Laboratory ESDP-LAB of the University of Palermo, in the framework of the European research project ASTONISH, was approved by the Ethics Committee of the University 'G. D'Annunzio of Chieti-Pescara (Italy) (n. 254 of 14 March 2017), partner of the project. The measurements reported in the manuscript were carried out on laboratory colleagues and students, properly instructed on the non-invasive procedure.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the subjects to publish this paper. Also, all efforts have been made to protect participant privacy and anonymity.

Data Availability Statement: Data are available on request.

Acknowledgments: The authors would like to thank the group of participants in this pilot study: Giuseppe Greco, Leonardo Mistretta, Raimondo Rizzo, and Vittorio Buscemi.

Conflicts of Interest: The authors declare no conflicts of interest.

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