

TEACHING INNOVATIONS

A remote laboratory course on experimental human physiology using wearable technology

Patrick Mayerhofer, James Carter, and J. Maxwell Donelan

Department of Biomedical Physiology and Kinesiology, Simon Fraser University, Burnaby, British Columbia, Canada

Abstract

To help educators deliver their physiology laboratory courses remotely, we developed an inexpensive, customizable hardware kit along with freely available teaching resources. We based the course design on four principles that should allow students to conduct insightful experiments on different physiological systems. First, the experimental setup should not be constrained to laboratory environments. Second, students should be able to take this course without prior coding and electronics experience. Third, the hardware kit should be relatively inexpensive, and all other resources should be freely available. Fourth, all resources should be customizable for educators. The hardware kit consists of commercially available electronic components, with a microcontroller as its hub (Arduino friendly). All measurement systems can be assembled without soldering. The hardware kit is cost-effective (approximately the cost of a textbook) and can be customized depending upon instructional needs. All software is freely available, and we share all necessary codes in open-access online repositories for simple use and customizability. All lab manuals and additional video tutorials are also freely available online and customizable. In our particular course, we have weekly asynchronous physiology lectures and one synchronous laboratory session, where students can get help with their equipment. In this article, we only focus on the novel and open-source laboratory part of the course. The laboratory includes four units [data acquisition, ECG, electromyography (EMG), activity classification] and one final project. It is our intent that these resources will allow other educators to rapidly implement their own remote physiology laboratories or to extend our work into other pedagogical applications of wearable technology.

laboratory; open source; physiology; remote; wearables

INTRODUCTION

Delivering effective laboratory experiences in science, technology, engineering, and mathematics (STEM) is challenging to do remotely. A goal of laboratory courses is to provide students with hands-on experience using methods and approaches relevant to the course area. In conventional laboratory courses, this hands-on experience is often enabled with the use of a small number of relatively expensive and specialized laboratory equipment in a face-to-face setting. The expensive and nonportable nature of traditional equipment make it challenging to replicate the experimental approach in a remote learning environment. That is, it has been easier to bring the students to the laboratory than the laboratory to the students. Consequently, although there is a substantial body of evidence about the effectiveness of online teaching in general (1), a commonly held view is that online teaching methods in laboratory courses are not equivalent alternatives to conventional laboratory experiences (2–4).

Compared with other disciplines in human biology, it has been especially challenging to identify appropriate remote laboratory teaching methods for physiology. In anatomy, for example, instructors can use interactive visualization to increase student engagement and learning (5, 6). In histology, virtual

microscopy offers an efficient learning tool with high performance outcomes and high student satisfaction (7–9). In physiology, the available tools are not as effective. For example, computer simulations can enhance the understanding of physiological concepts (10), but there are several reasons why not even high-fidelity patient simulators—which are lifelike computer model-driven manikins—can replace traditional teaching methods where students do physiological measurements on humans and other biological systems. These reasons include that reproducing realistic physiological scenarios can be difficult, time consuming, and expensive (11). Recently, educators have proposed smartphone-assisted physiology laboratories, where students can learn to measure different physiological parameters such as heart rate or respiratory rate with their own smartphones (12). Although this creative approach has many strengths, it constrains potential physiological experiments to those that are possible with phone sensors, which is a small subset of those that would normally be possible in on-campus laboratories. The lack of options for remote hands-on physiology laboratories became particularly clear to us during the COVID-19 pandemic when safety necessitated that we cancel all face-to-face classes for more than a year.

To help educators deliver hands-on physiology laboratory courses remotely, we developed an inexpensive, customi-

zable hardware kit along with fully open-source teaching materials. Our main goals were to deliver an open-source course that teaches physiology students how to do hypothesis-driven physiological experiments and to make the course inexpensive and customizable for educators with different needs. We designed it so that students without prior coding or electronics experience would find the course material approachable. To make the hardware kit inexpensive and customizable, it consists of commercially available electronic devices and components with a microcontroller as its hub and includes a suite of physiological sensors. With customizable laboratory manuals and supplementary video tutorials, students measure physiological signals such as electromyography (EMG), electrocardiography (ECG), and kinematics. Then, they analyze and interpret the acquired signals with open-source computer software available through source code repositories. In this article, we mainly focus on the novel part of this course, the laboratory portion. The laboratory portion includes the hardware, software, and pedagogical resources that we developed. Educators can use these resources to teach a stand-alone laboratory course and a laboratory portion for a hybrid lecture and laboratory course.

MATERIALS AND METHODS

Course Design Principles

We had several key principles for the design of the course. First, the hardware system underlying the data collection must be wearable. That is, all sensor configurations could be worn on the body and operated without the necessity of a computer connection, using battery power and data logging capabilities.

Second, extensive technical experience must not be a prerequisite for the course. Toward this principle, setting up the hardware should work without soldering and the number of wires and devices for a measurement system should be small. Additionally, students should not require prior coding knowledge to set up software for the measurement systems as well as the data analysis. Third, all resources must be financially accessible. The hardware kit should be relatively inexpensive (approximately the cost of a textbook), all the software required should be open source, and the instructional materials should be open access. Fourth, the workload for educators to develop a similar course must be minimal. All hardware, software, and instructional materials should be customizable. Finally, the combination of these resources must allow students to do multiple insightful experiments on a range of physiology systems. Based on these principles, we demonstrate our solutions for the hardware kit, software, and instructional materials and explain how to customize them to meet different needs.

Hardware Kit

The hardware kit consists of commercially available electronic components, with a microcontroller as its hub and a suite of physiological sensors (Table 1). To make the hardware kit wearable, a 9-V battery powers the system and a data logger stores the data on a memory card, eliminating the need to be tethered to a computer. To make the system solderless, the devices connect either via jumper wires or via a specific one-wire protocol called “Qwiic”(13). With the digital and analog input pins and the Qwiic connection, the microcontroller can connect to many state-of-the-art electronic devices without the need to solder. This allows

Table 1. Overview of the materials used in the hardware kit

Component	Cost, \$US	Model	Relevant Specifications
Microcontroller	~20	SparkFun RedBoard Qwiic	Input voltage: 7–15 V Digital and analog input pins One Qwiic connector
Analog-digital converter	~10	SparkFun Qwiic 12 Bit ADC	Operating input voltage: 2–5.5 V 12-bit resolution Programmable input gains
Data logger	~17	SparkFun Qwiic OpenLog	Two Qwiic connectors Data logging at 20 kb/s Compatible with 64 MB to 32 GB micro SD cards (FAT16 or FAT32)
Micro SD	~7	Any	Two Qwiic connectors 64 MB to 32 GB FAT16 or FAT32
Accelerometer	~12	SparkFun Triple Axis Accelerometer Breakout—MMA8452Q (Qwiic)	Operating input voltage: 1.95–3.6 V Input range: ±2 g/±4 g/±8 g Sampling frequency: 1.56–800 Hz 12-bit resolution
EMG/ECG sensor setup	~43	Grove EMG Detector Kit	Two Qwiic connectors Operating input voltage: 3.3–5 V Output voltage: max 3.3 V
12 additional electrodes	~2	Any	With Snap Connector
9-V battery holder	~3	Any	Standard 5.5 × 2.1-mm, center-positive barrel jack
9-V battery	~4	Any	
USB to micro-B cable	~5	Any	Preferably >1 m
Three Qwiic cables	~3	Any	
Ten jumper wires	~1	Any	
Carton box	~1	Any	
Total	~128		

EMG, electromyography; ECG, electrocardiography.

educators to customize the hardware kit with different sensors depending upon instructional needs. The particular hardware kit that we are using (Fig. 1) is ~\$130 US. In comparison, current human physiology testing kits used for conventional undergrad laboratory courses cost ~\$6,000 US per kit (e.g., iWorx Systems Inc.). This system can measure ECG and EMG at a sampling frequency of up to 1,000 Hz and three-dimensional accelerations with a range of up to ± 8 g and a sampling frequency of up to 800 Hz, all at a resolution of 12 bits. When untethered from a computer, the maximum sampling frequency reduces to ~50 Hz.

Software and Software Repositories

We chose Arduino software to program the hardware, Python programming language for data analysis, and GitHub as the online repository. As the microcontroller is an Arduino-compatible development board, we chose Arduino IDE (Integrated Development Environment, Arduino LLC) to be the programming platform. Arduino IDE is an open-source platform that uses C and C++ programming language and is commonly used for programming microcontrollers of this type. Python (Python Software Foundation) is an open-source programming language. As one of the most-used and fastest-growing programming languages in recent years, Python offers simple-to-use features and a great online community for support (14). GitHub (GitHub, Inc.) is a state-of-the-art platform for source code management. Its basic services are free of charge. Programmers use it for collaborative projects and to offer their software to the general public. For

each laboratory of this course, we uploaded relevant source codes and example data to a GitHub repository (15–18). We made the repositories open access for everyone, so that students can download the software, customize it if needed, and use it for their own projects. If educators want to customize the repository, they can download and edit the source codes. Educators may then add their own additional source codes and upload their collection to their own repository. Arduino IDE, Python, and GitHub are industry standards and not simplified tools for educational purposes only. Consequently, students learn how to use tools that can be applied in their subsequent careers.

Instructional Material

We used Google Docs for the laboratory manuals and assignments, and YouTube for supplementary video tutorials. Google Docs (Alphabet Inc.) is an open-access online word processor that allows multiple users to collaborate and edit files in real time. Additionally, Google Docs allows for document sharing with a defined group of people or web publishing to make it visible for everyone on the web. Educators can copy the laboratory manuals or assignments or the parts of them they need. They can then customize a document for their own course and share it with their students or the general public. To help students set up measurement systems and analyze data, we created a YouTube channel with supplementary video tutorials (19). To customize this library, educators can create their own YouTube library with videos from the channel and their own additional content.

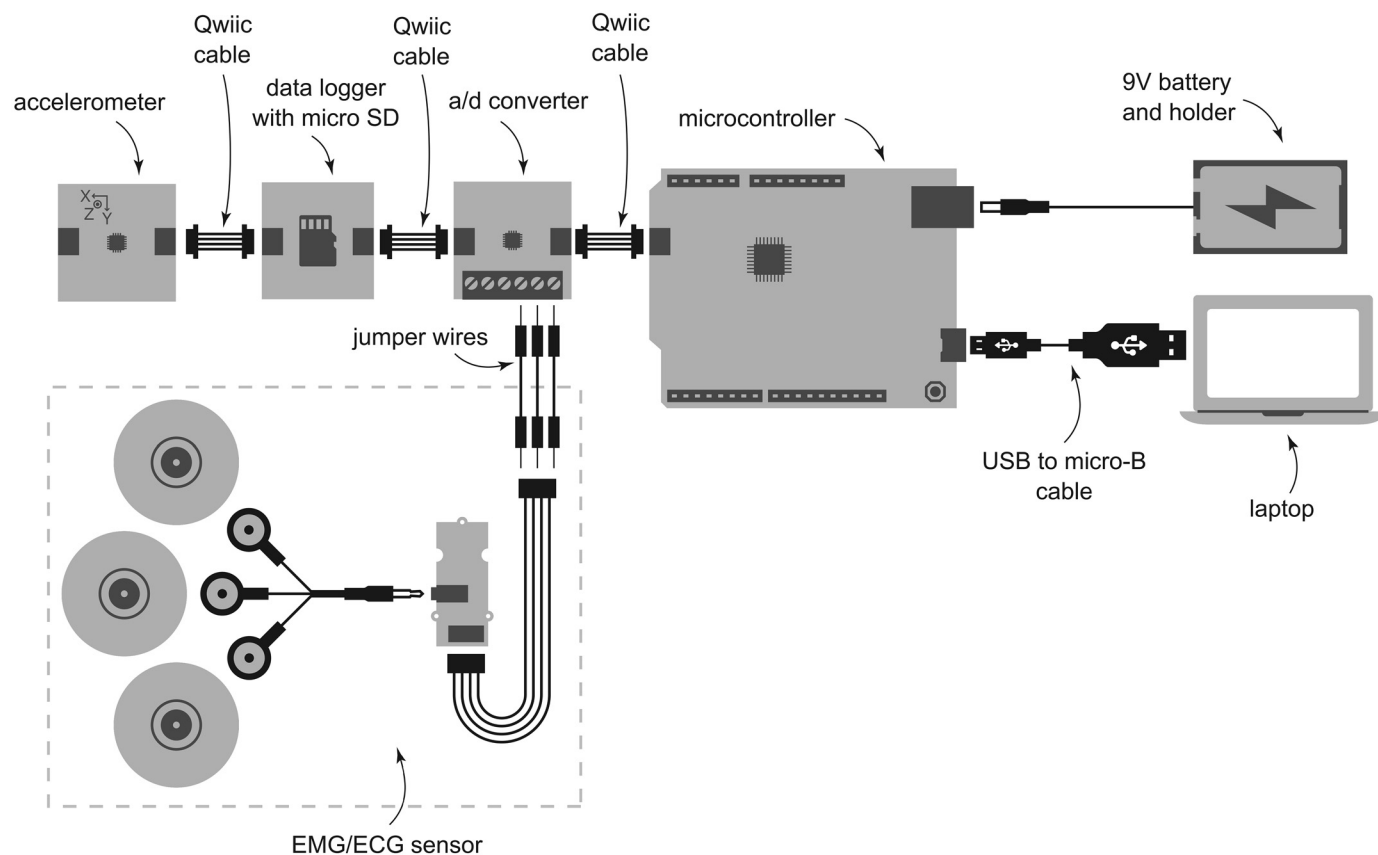


Figure 1. Components of the hardware kit. EMG, electromyography; ECG, electrocardiography.

RESULTS

Beginning in Fall 2020, we have been using these laboratory resources to teach our fourth-year physiology course remotely in the Department of Biomedical Physiology and Kinesiology. We coordinate with a local electronics store, which prepares and ships all hardware kits to our students before the semester starts (Fig. 1). In asynchronous weekly lectures and tutorials, we teach students systems physiology concepts and how to measure and analyze physiological systems. The lecture topics include Wearable Technology, Data Acquisition, Blood Pressure, ECG, Heart Rate and Heart Rate Variability, Exercise Intensity and $\dot{V}O_{2\max}$, EMG, EEG, Activity Quantification, Pulmonary Function, and Temperature. For the laboratory component, we include five laboratory units: data acquisition, ECG, EMG, fitness tracking, and final project (20). Students have 3 wk to finish each unit and work in small groups of three or four members, with each group member working from their own home. To support students during their laboratories, we hold weekly 3-h-long synchronous online laboratories, where students can ask questions and teaching assistants can help with troubleshooting. For each of the four laboratories, students submit a laboratory report, and for the final project they have to submit a conference-style video presentation. This course was conducted within Simon Fraser University teaching instruction and research policies.

In the first laboratory, students use the accelerometer and the data logger to learn the principles of data collection, analog/digital conversion, data processing, and data storage (Fig. 2) (21). In multiple small experiments students first collect accelerometer data while being tethered to the computer to both power the system and store data. In the wearable version, they power the system with a 9-V battery while logging the data to a memory card. With the collected data, students then learn how to filter and interpret the data.

In the second laboratory, students set up a 1-lead ECG measurement system to collect raw ECG data and learn about heart rate, heart rate variability, and exercise intensity (Fig. 3) (22). Students put the two measurement electrodes on the manubrium and on the left V6 ECG placement

position and the reference electrode on the C₇ vertebra. In a resting experiment, students collect the data while tethered to the computer, to allow for higher sampling frequency. In an exercise experiment, students use the wearable system while doing intervals of higher and lower intensities on either a stationary or outdoor bike. For both the resting and exercise experiments, students detect the R-wave peaks with an algorithm in Python. Based on the R-wave peak intervals from the resting data they then calculate their resting heart rate and heart rate variability, and based on the R-wave peak intervals from the exercise experiment they visualize their continuous heart rate and predict energy expenditure.

In the third laboratory, students learn how to collect and filter raw EMG data and how to analyze muscle fatigue by calculating and interpreting a frequency spectrum (Fig. 4) (23). Students collect EMG data from the biceps muscle while holding different weights and doing maximum voluntary contractions (MVCs). In Python, students preprocess the EMG data and calculate the relative muscle activations when holding different weights. With the MVC data, students calculate muscle fatigue. They isolate three 0.5-s windows, one in the beginning, one in the middle, and one in the end of the burst, and calculate the median frequency that splits the integral of a power spectrum into two equal halves. To see how the muscle fatigues, they then compare the median frequency of the respective time windows.

In the fourth laboratory, students learn how to build a wearable, battery-powered fitness tracker that measures wrist accelerations, automatically classifies different activities, and counts steps (Fig. 5) (24). With a self-built wearable accelerometer on their wrist, students collect acceleration data during lying, standing, walking, and running. In Python they then label their own data. Every student uploads their labeled data to a shared folder. Each group trains a neural network model for activity classification with the data of the other groups and tests the accuracy of the activity classification model on their own group's data. Additionally, students develop a simple step-counting algorithm by high-pass filtering the acceleration data and finding the peaks.

In the final project, students identify an interesting physiological question. They generate hypotheses, develop and

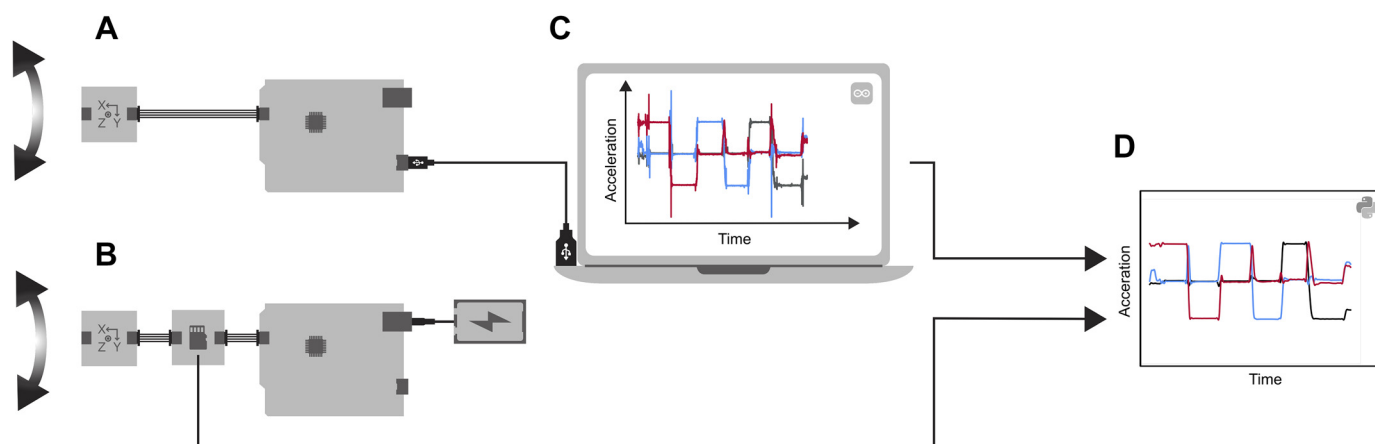


Figure 2. Graphical representation of the workflow for the data acquisition unit. *A:* the setup while being tethered to the computer. *B:* the wearable version with the 9-V battery and the data logger. *C:* 3-dimensional raw acceleration data as collected by the hardware. *D:* 3-dimensional, in Python, filtered acceleration data.

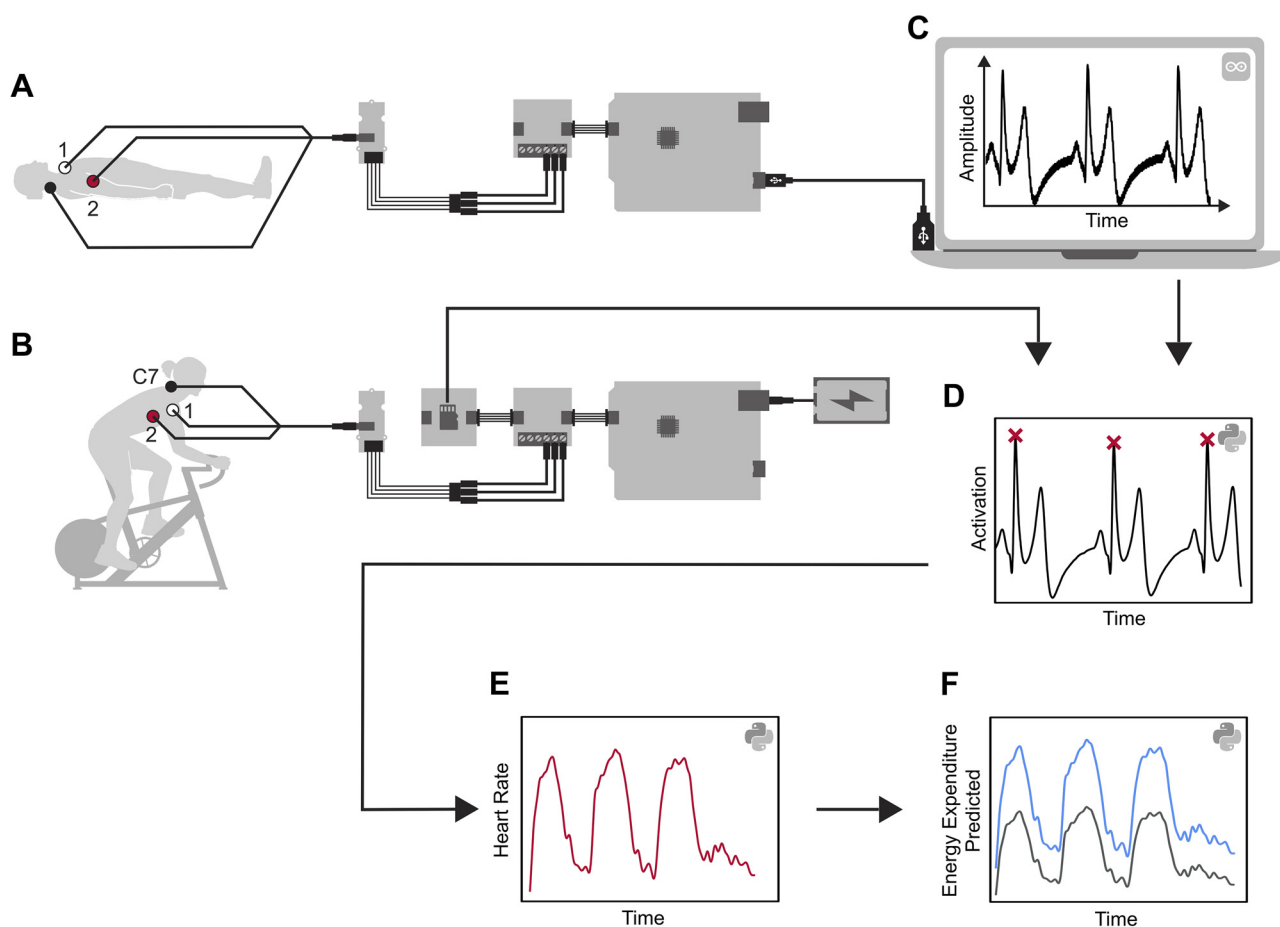


Figure 3. Graphical representation of the workflow for the ECG unit. *A*: the resting experiment setup, with the 3 electrodes, while being tethered to the computer. *B*: the wearable setup. *C*: the raw ECG data as collected by the hardware. *D*: the detected R-wave peaks in Python. *E*: continuous heart rate during the exercise experiment in Python. *F*: the predicted energy expenditure in Python.

perform their own experiments, and analyze and interpret the data to test their hypotheses and answer the original question. For example, one group in the first semester compared the heart rate and heart rate variability between rest and watching a scary video. Another one compared the EMG of doing squats with differently positioned feet. We also allowed for more technological projects. One group, for example, tried to evaluate the accuracy of a self-built accelerometer-based device that measures jump height. For the experiment, each group member would collect the data on themselves. They could then analyze data of three or four people and interpret the results accordingly.

To assess the students, we use a combination of online quizzes, assignments, and writings. Before each weekly synchronous online laboratory session, students have to do a 10-min-long quiz with 5–12 questions. We include questions about the physiological systems and about the laboratory tasks to evaluate students' knowledge from the physiology lectures as well as from the laboratory parts, respectively. For each of the four laboratory units, students have to submit an assignment, in which they have to answer questions about the laboratory tasks, and submit their own collected and analyzed data sets. For the final project, students submit a formal proposal of their project about halfway through the semester. Toward the end of the semester, they then submit

a journal-style paper and a conference-style presentation. We review the proposal and help them revise it to be both feasible and useful. We assess the journal-style paper based on an extensive marking rubric. Students have to demonstrate their background knowledge of the topic, the relevance of their project, a clear description of the methods, insightful results, and a thoughtful discussion. For the presentation, we also assess their clarity and presentation skills. We do not assess the students' knowledge through exams.

To assess the students' perception of the course, we use standard university student evaluation forms at the end of the semester and weekly anonymous feedback forms throughout the semester. Our perception after three semesters is that students find the course challenging but valuable. As expected, most students do not have prior experience with electronics and coding. Our general impression—based on student evaluations at the end of the semesters as well as speaking with students throughout the semester—is that most students find the practical component difficult but worthwhile and perceive the workload as being high. For example, one student reported: “My only complaint about this course was the time commitment. Overall, the hands-on aspect helped me learn more effectively than any other course I've taken.” Another student reported: “This was one of the most challenging BPK [Department of Biomedical Physiology

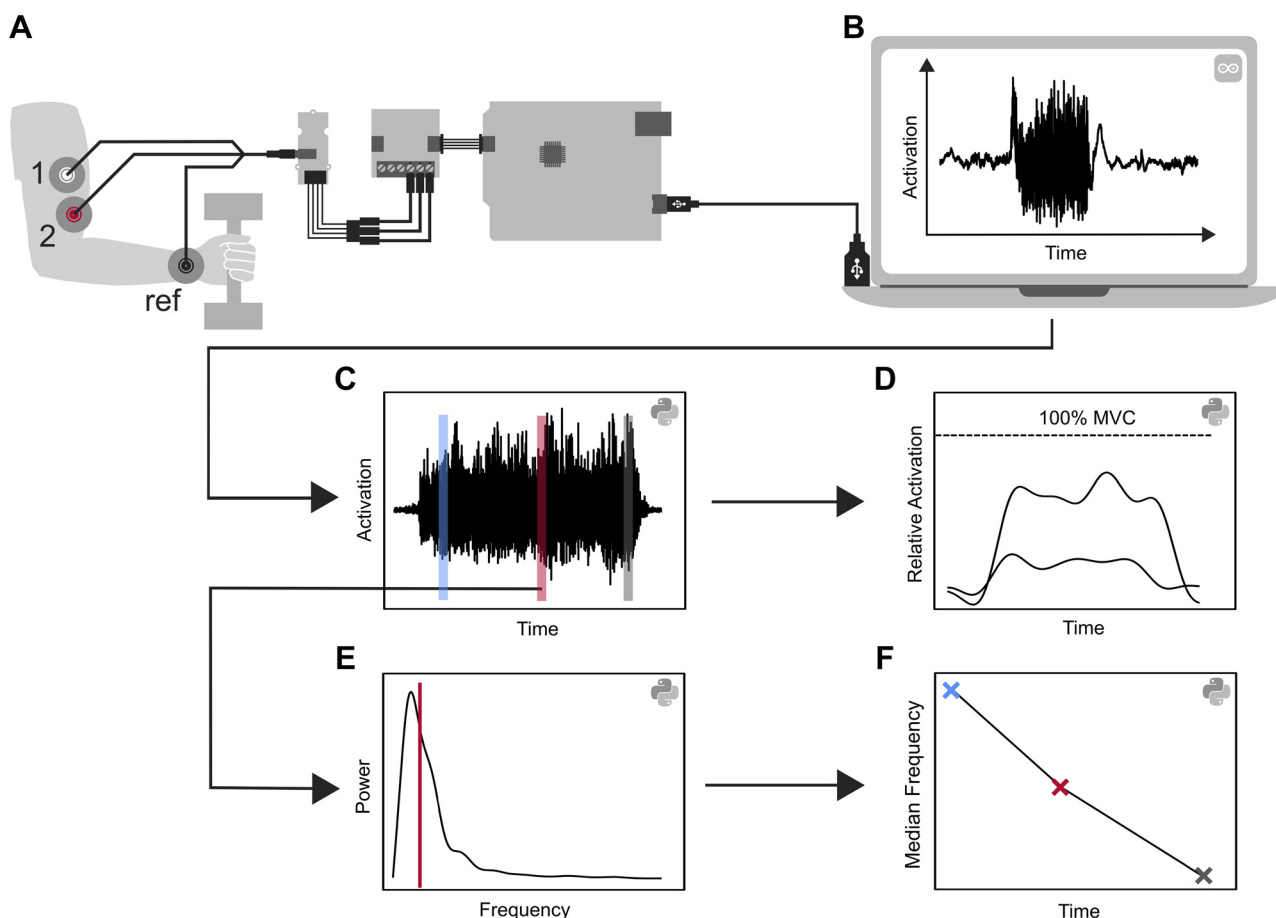


Figure 4. Graphical representation of the workflow for the EMG unit. *A*: the setup with the 2 measurement electrodes on the biceps and the reference electrode on the wrist. *B*: raw EMG data of a single burst as collected by the hardware. *C*: the preprocessed EMG data and the 3 isolated windows at the beginning, middle, and end of the burst in Python. *D*: the relative muscle activations when holding different weights in Python. *E*: the median frequency that splits the integral of a power spectrum into 2 equal halves in Python. *F*: the change in median frequency of the respective time windows in Python. MVC, maximum voluntary contraction.

and Kinesiology] courses I've had to take in my undergraduate studies. In the end, I can genuinely say that I enjoyed the course even if I wasn't the best at using Python." Students perceived the videos to be crucial for their success. For example, one student reported: "The course was very well done considering the conditions. Bugs were frequent and frustrating working with the electronics and coding, but the videos were lifesaving." Overall, our impression was that despite the major time commitment and the many difficulties associated with a first-time course offering, students valued this new and innovative approach to hands-on, remote, and experiential learning about physiological systems and how to study them.

Quantitative evaluations in the student evaluation forms were positive. In total, 107 students took and evaluated this course in the first three consecutive semesters of offering the course. Students had to score four statements between 1 and 5, with 1 being complete disagreement and 5 being complete agreement with the statement. The first statement was "The different course activities/components (lectures, discussions, assignments, etc.) were connected" and scored on average 4.12 (SD 0.9). The second statement was "Course activities/components (lectures, discussions, assignments, etc.) helped me learn" and scored on average 4.27 (SD 0.88).

The third statement was "Course materials (textbooks, library articles, and website links) improved my understanding of the course content" and scored on average 4.13 (SD 0.99). The fourth statement was "The assessments in this course (tests, assignments, essays, etc.) allowed me to demonstrate my understanding of the course content" and scored on average 4.11 (SD 0.79).

DISCUSSION

Although this approach to remote learning has many positive attributes, it also has several limitations. First, the performance of the measurement systems is limited. Particularly for EMG and ECG measurements, expensive laboratory equipment will provide more accurate and reliable data. Second, this course requires a specialized skill set from its teaching assistants. To support students, teaching assistants not only need to understand the underlying physiology but also need to understand the hardware and software used in this course. We solved this problem with two mechanisms: New teaching assistants got an introduction to the resources before the semester starts, and former, experienced teaching assistants were available for any additional help if the current teaching

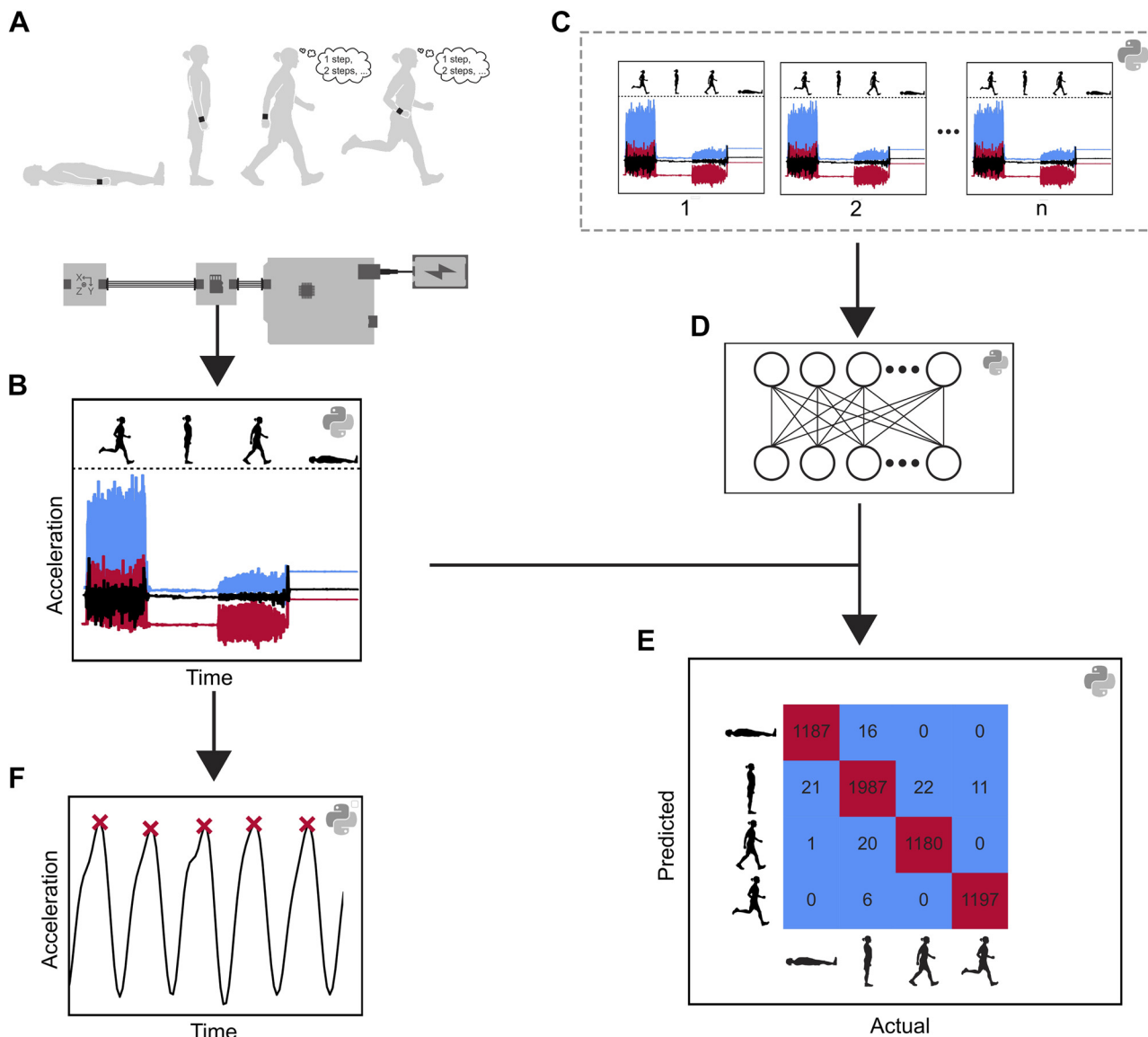


Figure 5. Graphical representation of the workflow for the activity classification unit. *A*: the wearable setup of the fitness tracker. *B*: 3-dimensional raw acceleration data during running, standing, walking, and lying in Python. *C* and *D*: students use the collected data sets of their classmates (*C*) to train their own neural network in Python (*D*). *E*: the confusion matrix result when testing the trained neural network's accuracy with the student's own data from *B* in Python. *F*: the low-pass filtered acceleration data with the found peaks at each step of their walk or run in Python.

assistants needed guidance. Third, troubleshooting is challenging and time intensive. Teaching assistants have to help students troubleshoot hardware and software problems via online meetings, which is not as effective as in-person support, and sometimes not sufficient. To ameliorate this limitation, we always provided example data via the GitHub repositories in order for students to continue their analysis even if they could not finish data collection. And finally, students without prior coding experience appeared to have a significantly harder time in finishing the programming parts of the laboratories compared with more experienced students. An effective, but incomplete, solution was for students to watch several Python and Arduino introduction tutorials before the start of the first laboratory.

We envision that this course will complement rather than replace conventional, hands-on laboratory courses. Conventional, on-campus laboratory courses currently have two

main advantages. First, laboratory systems generally provide better measurement accuracy and reliability compared with wearables (25). It is important for students to learn how to use these gold-standard measurement systems, specifically for those who want to follow a career in experimental physiology. And second, teaching laboratory courses on campus allows educators to more efficiently support students during the laboratory sessions, like, for example, when helping students during troubleshooting.

Compared with conventional laboratory courses, this approach offers several new opportunities. In conventional laboratories students typically work in groups, because there is a limited number of measurement devices. In this remote version, every student has their own laboratory kit, allowing each student to use the equipment and learn to collect data. This increases the overall data collected during a laboratory unit and provides the opportunity to do large studies by class-

sourcing data (e.g., activity recognition experiment in *unit 4*). The customizability of the resources can help educators to use this laboratory kit in several different courses in multiple departments. Whereas we used it to teach how to do physiological experiments, it may instead be used in a hands-on engineering course. This opens the possibility of interdisciplinary courses in which students from different disciplines learn together. The customizability also enables students to innovate on the provided resources to design and test their own ideas. For example, students from physiology, engineering, and business could collaborate in an entrepreneurship course, where they develop a business to go along with the research and development of their wearable sensor product.

ACKNOWLEDGMENTS

We thank the Department of Biomedical Physiology and Kinesiology as well as the students, lecturers, and teaching assistants for supporting us during the development of this course, specifically Pavreet Gill, our first teaching assistant, who not only greatly supported all students in the first two semesters of teaching this course but also helped us to optimize this course in various ways. We also acknowledge and thank Karam Elabd, who was the first instructor who taught this course without being involved in its development. Karam and his teaching assistant, Omid Vakili, did a great job in continuing a culture of continuous improvement and feedback, which greatly helped fine-tune the course even further.

GRANTS

This work was supported by National Sciences and Engineering Research Council (NSERC) Discovery Grant RGPIN-2020-04638 to J.M.D.

DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the authors.

AUTHOR CONTRIBUTIONS

P.M., J.C., and J.M.D. conceived and designed research; P.M. performed experiments; P.M. analyzed data; P.M., J.C., and J.M.D. interpreted results of experiments; P.M. prepared figures; P.M. drafted manuscript; P.M., J.C., and J.M.D. edited and revised manuscript; J.C. and J.M.D. approved final version of manuscript.

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