

Bringing Wearable Sensors into the Classroom: A Participatory Approach

By bringing research into the curriculum, this article explores new opportunities to refresh some classic signal processing courses. Since 2015, we in the Electrical and Electronic Engineering (EEE) Department of Imperial College London, United Kingdom, have explored the extent to which the level of student engagement and learning can be enhanced by inviting the students to perform signal processing exercises on their own physiological data. More specifically, using new wearable sensor technology and video instructions as an experiment guide, the students are asked to record their electrocardiograms (ECGs) and perform both time- and spectral-domain estimation tasks on their own real-world data. In this way, the students not only gain experience with recording hardware and sources of signal contamination (baseline wanders and artifacts), but they also are highly motivated by being kept in the loop and through their part ownership of their course.

In addition to bringing biopresence into the curriculum, this approach has also broadened the students' perspective on research and employment opportunities in, among others, next-generation health care. All of the material necessary to implement this coursework can be found at www.commsp.ee.ic.ac.uk/~mandic/Biopresence_Material.htm.

Motivation

The recent advances in sensor technology and the fast-evolving way in which we generate, process, and revise information

is bound to have a major impact on how we teach and learn. Given the relative maturity of the signal processing field and the availability of competing multimedia educational resources, a common challenge in modern signal processing education is to strike a balance among the background physics intuition, mathematical rigor in lectures, practical relevance of the material, and student engagement. This tradeoff arises from both the diversity in student learning styles and the requirements imposed by the future careers of these students.

For example, M.Sc. courses typically attract students from vastly different backgrounds, while at Imperial College we encourage students to take cross-departmental courses (EEE, computing, bioengineering, etc.); this both requires particular care not to be EEE specific and adds further difficulty in creating one-size-fits-all course material. In addition, in an advanced signal processing (ASP) course, we prefer to include elements that prepare the students for jobs that may not even currently exist but will be in much demand in the next four to five years [1].

The increasing exposure to popular technological advancements, such as big data, the Internet of Things, and wearable devices, is naturally asking questions about the relevance of some classic subjects in modern real-world applications [2]. In other words, it cannot be assumed that students will be able to appreciate the scope of their courses without explicitly building a bridge between the material in lessons and cutting-edge research. This all calls for more effort in bringing research into the classroom. From our

own experience, it is biopresence that not only has a broad spread of signal processing demands but is most convenient to implement and most enjoyed by the students.

Recent articles on signal processing education aim to demystify and unify some compulsory material in signal processing courses [3]–[5]. Our aim here is to reflect on the opportunities provided by the recent sensing technologies [6] and, in doing so, meet the demands of the new technologically orientated classroom. Indeed, standard signal processing courses were developed with radar, array processing, and communications problems in mind (all of which require EEE-specific knowledge); however, to maximize the impact of our area we ought to facilitate the adoption of signal processing tools by other areas, such as bioengineering [7], [8].

Our approach focused on inviting the students to collect and analyze their own physiological data (ECG and respiration) using the latest signal acquisition devices, enabling students to

- 1) apply classic signal processing tools taught in the lectures to their practical assignments in a physically meaningful and fun way
- 2) appreciate the relevance of their degree with respect to technological advancements
- 3) take part-ownership of their taught courses
- 4) engage in curiosity-driven learning and explore feasible extensions and new applications of their taught material on their own data
- 5) become aware of ethical issues and the societal impact of their work.

In this article, we elaborate on the “signal processing for wearable health care” assignments for students enrolled in the courses 1) advanced signal processing (ASP) and 2) adaptive signal processing and machine intelligence (ASP-MI), both taught at a later stage undergraduate and postgraduate level in the Department of EEE at Imperial College London.

The course

Data analytics courses increasingly attract a wider profile of undergraduate and M.Sc. students from across engineering and computing areas, and for best learning outcomes, it is critical to strike a balance between mathematical rigor and principles of the physical world (e.g., signal-generating mechanisms). We do so through structured computer exercises, as illustrated in Figure 1. The proposed framework was designed to provide a stimulus for enquiry into the algorithmic requirements to achieve certain digital signal processing tasks, and, hence, the approach becomes a path to learning, discovery, and consolidation of knowledge. In our case, MATLAB assignments are designed so as to explore real-world applications in audio processing and biomedical and power engineering.

Signal processing for wearable health care

The emergence of inexpensive physiological sensors, which are currently embedded in advanced wearable devices, presents new opportunities for their use in real-time and continuous-health monitoring applications, with signal processing being the key enabling technology. For instance, the growing popularity of devices such as the Apple Watch and Fitbit are inspiring student engineers and entrepreneurs to develop novel applications for health-care purposes. These opportunities come with significant challenges related to the detection, estimation, and classification of relevant biomedical features.

To expose our students to these challenges and equip them with the necessary tools and analysis frameworks to address these issues, we have constructed an assignment that focuses on

extracting and analyzing both the heart rate and breathing rate of a person from his or her ECG.

In other words, as humans are beginning to merge with the technologies they have created, there is an urgent need to keep abreast with signal processing education and explore innovative and participatory ways to present the taught material to highlight the central role of signal processing as an enabling technology for many of these advances.

Why is the ECG so convenient?

Among the different physiological signals available for noninvasive recordings, we chose the ECG for several reasons. First, the ECG has significant value both in clinical and nonclinical applications because of the ease of interpretation, reliability, and physiological meaningfulness. In nonclinical applications, for example, the activity of the autonomic nervous system, which is

related to stress, can be estimated from heart rate variability (HRV), a time series obtained from the time difference between consecutive R-peaks in the ECG [9]. Figure 2 shows an ECG waveform with the corresponding P-, R- and T-waves. The time interval between consecutive R-peaks is referred to as the *RR-interval (RRI)*.

Besides the heart rate, RRIs can be used to obtain the breathing rate of a person through a phenomenon known as *respiratory sinus arrhythmia (RSA)*. In signal processing terms, breathing modulates the cardiac function by respiratory effort that can be readily observed by the acceleration of the heart rate during inhalation (breathing in) and the deceleration of the heart rate during exhalation (breathing out). In addition, the strength of RSA in an individual can be used to assess cardiovascular health and psychological stress [10].

Finally, an ECG trace can be easily obtained from a person without

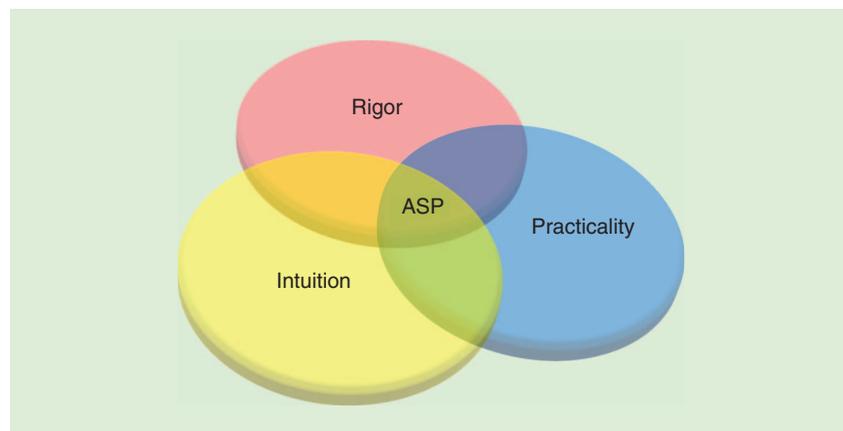


FIGURE 1. Striking a balance among mathematical rigor, engineering intuition, and practical applicability is a key challenge in the ASP curriculum.

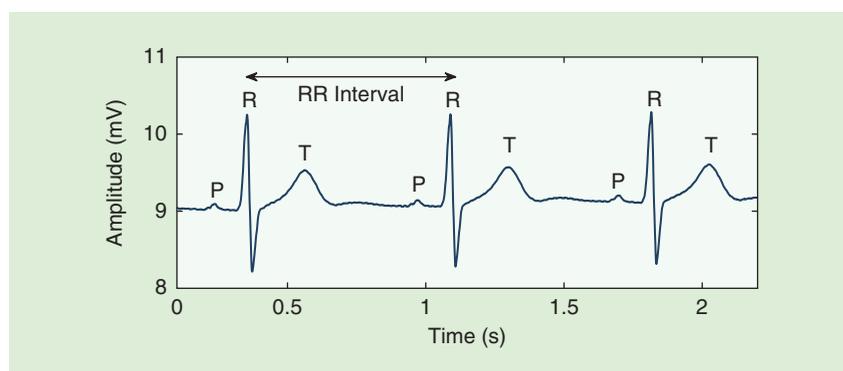


FIGURE 2. An example ECG trace with visible P-, R- and T-waves.



FIGURE 3. A convenient placement of electrodes on the forearms, for the recording of the ECG.



FIGURE 4. Our iAmp recording device against one U.K. pound coin (22.5 mm in diameter).

cumbersome setup procedures as it only requires a minimum of two electrodes to be placed on symmetric positions on a person's body with a third, ground electrode, located next to one of the sensing electrodes. For a good tradeoff between the ease of setup and strength of signal obtained, we instructed the students to place the electrodes on their forearms (see Figure 3).

Signal acquisition device: The iAmp

The key recording component that was instrumental to the success of this

assignment was our own custom-made portable signal acquisition device, referred to as the *iAmp* (see Figure 4). The *iAmp* is equipped with a 24-bit analog-to-digital converter (ADC) with a sampling frequency of up to 32 kHz ($f_s = 1$ kHz was used for our recordings), a microprocessor, and a secure digital (SD) card slot to store the data. While the *iAmp* is designed to record any bio-potentials (e.g., ECG, electroencephalogram, and electromyogram) from up to eight channels, in our experiment, it was only used to record the ECG.

The distinguishing features of the *iAmp* that contributed to its deployment in our assignments are its portability, “hackability,” and the simple input–output (I/O) interface. For example, the settings for the *iAmp* can be changed by the students, as the configuration file is stored on its SD card memory. Furthermore, without the *iAmp*, it would not be economically feasible for us to design this coursework, as commercially available biopotential recording devices are cost-prohibitive for educational applications. For example, based on our market analysis, 15 commercially available ECG recording devices (the number of *iAmps* used in our course) would have cost the university approximately US\$60,000. (This information is based on the Avatar ECG recorder, which costs approximately US\$4,000 per device; see www.egi.com/research-division/research-division-research-products/avatar for more information.) With our own in-house built *iAmp*, on the other hand, we were able to give the students a hands-on experience of the state of the art in wearable vital signs monitoring devices at a fraction of this price, and in a natural way.

Experimental setup

Before the start of the experiments, the students are briefed on the principles of cardiac electric potentials and about any potential health hazard or discomfort. Building upon their engineering background, they are taught how cardiac electric potentials are generated by currents in the heart muscle and how potential differences between two points on the body surface are measured (see Figure 5).

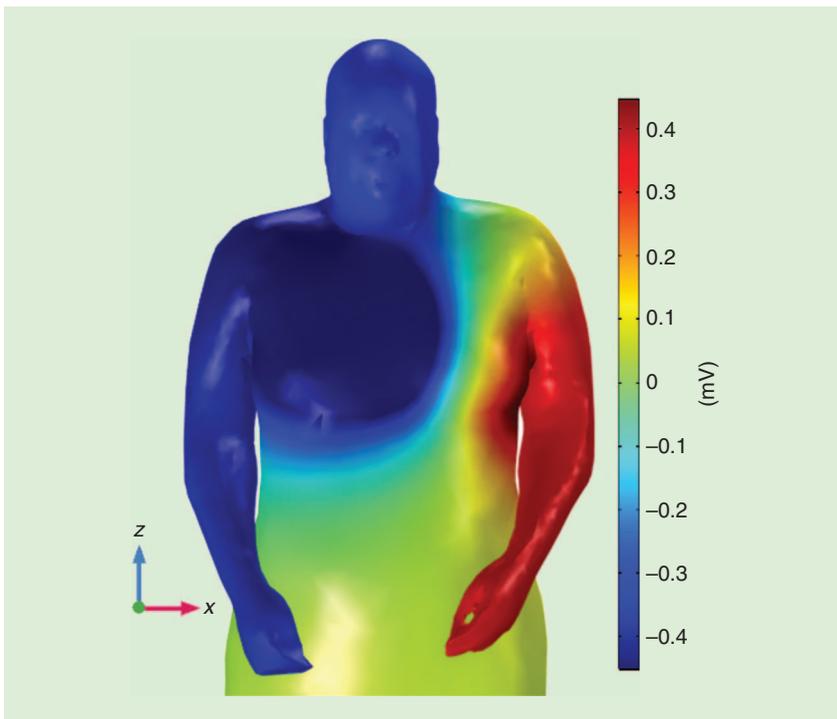


FIGURE 5. Cardiac potentials on the body surface at the approximate timing of an R-peak in the ECG cycle. (Figure produced with COMSOL Multiphysics software.)

In the data collection stage, the students are required to record their own ECG for a period of 12 min while being seated. We have also found that students preferred on-screen instructions to a hard-copy. To this end, we have created a short video that runs on a loop on the main screen in the lecture room, which explains the practical settings such as positions of the electrodes, connections of the leads, and general equipment handling.

A second video is accessed by students from their laptops. This guides the students through three experiment trials, whereby in each trial the students are required to breathe at different rates, as per the on-screen instructions:

- trial 1: Unconstrained breathing for 4 min
- trial 2: Constrained breathing (fast) at 25 breaths per minute for 4 min
- trial 3: Constrained breathing (slow) at 7.5 breaths per minute for 4 min.

Screenshots of the on-screen instructions from our computer video, which guides a student through the experiments, are shown in Figure 6. To simplify the experimental setup, all of the trials are recorded within one 12-min long

session (3 × 4 min). For conveniently distinguishing between parts of the experiment, students were instructed to tap the electrodes (leading to artifacts) between

the trials. These artifacts, in addition to the timing of the trials, assisted the students in segmenting their data into three separate data vectors. Figure 7 shows a

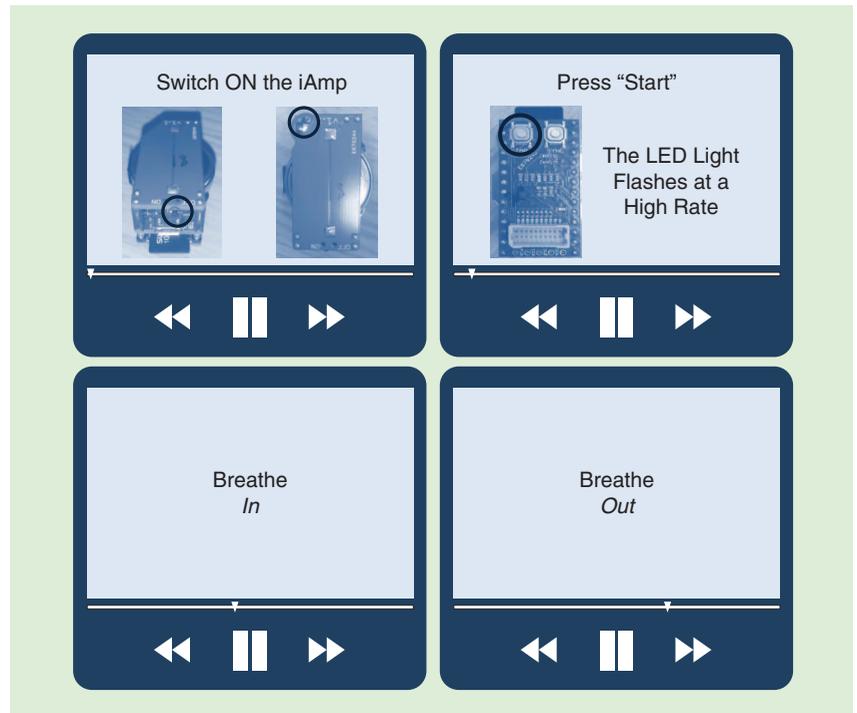


FIGURE 6. On-screen video instructions that guide the students through the experiments.

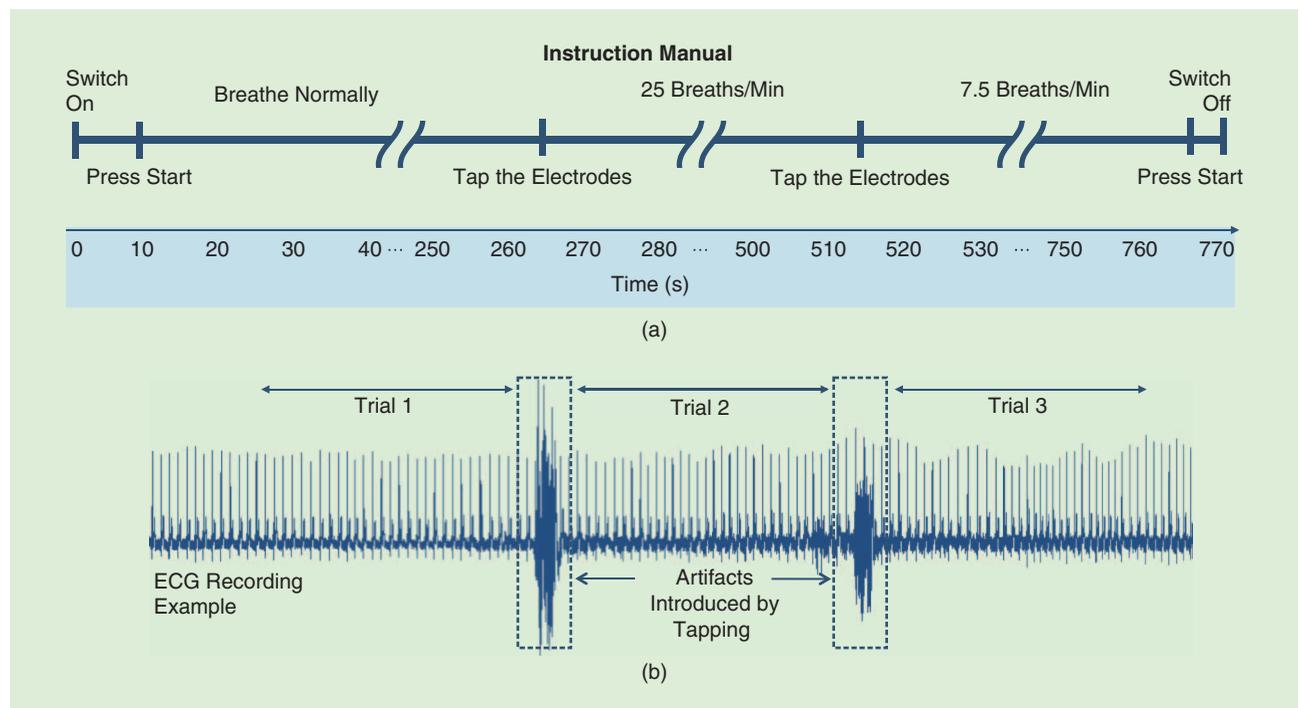


FIGURE 7. The recording instructions and an example of a recorded ECG. (a) The time sequence of the real-world ECG recordings. (b) Three trials at different breathing rates with transition periods in between. The unconstrained breathing (Trial 1, left) shows no obvious effects of the modulation of the ECG by respiration, while the ECG recorded while breathing at fixed rates (Trials 2 and 3, middle and right) shows clear effects of the RSA, a sinusoidal modulation of the ECG envelope by respiration.

summary of the experimental instructions and a sample ECG recording that corresponds to the different trials outlined previously. Observe the sinusoidal modulation effects of the respiration on the ECG envelope in trials 2 and 3 in Figure 7(b); a perfect vehicle to incorporate

the random modulation/demodulation background into a biosignal analysis task.

Preprocessing

The raw ECG recordings from the iAmp typically exhibit baseline drifts and other artifacts that often interfere

with the analysis conducted by the students. Figure 8(a) shows an example of an ECG recording that contains low-frequency drifts. As an optional exercise, the students are asked to design a digital filter to remove unwanted drifts to yield a clean signal that resembles a “clinical” ECG reading, such as the ECG trace in Figure 8(b).

To simplify the preprocessing steps, we also provided MATLAB scripts to identify the heartbeats (R-peaks) in the ECG and to generate the RRI time series (in a way similar to that in [11]), as the main focus of the assignments was on processing the respiratory data and variations of the heart rate in the frequency domain and not on artifact removal. In the preprocessing step, the MATLAB script first performs band-pass filtering of the raw ECG recording with a fourth-order Butterworth filter with cutoff frequencies at 5 and 20 Hz. This removes high-frequency noise and low-frequency fluctuations, while also suppressing some features of the P-, S-, and T-waves to assist the RR-interval detection.

In the next step, R-peaks are detected in the signal based on an amplitude threshold (the broken blue line in Figure 9), which can be adjusted by the student. The so-identified peaks and the obtained RRI time series are similar to the example shown in Figure 9; the students were able to fine-tune the detection parameters to suit their own recorded data. Next, the provided MATLAB script identified suspected anomalies in the ECG traces (e.g., the ectopic peaks) and students were given the option to discard them. Finally, the RRI time series was resampled at a sampling frequency of 4 Hz, to produce the interpolated time series suitable for further analysis.

The assignments

To illustrate the usefulness of the adopted data-driven approach as a complement to the standard theory-based teaching, we revisited the concept of biased estimators from the perspective of probability density functions of weighted average heart rates [12, Problem 2.4]. In the problem, the notion of heart rates

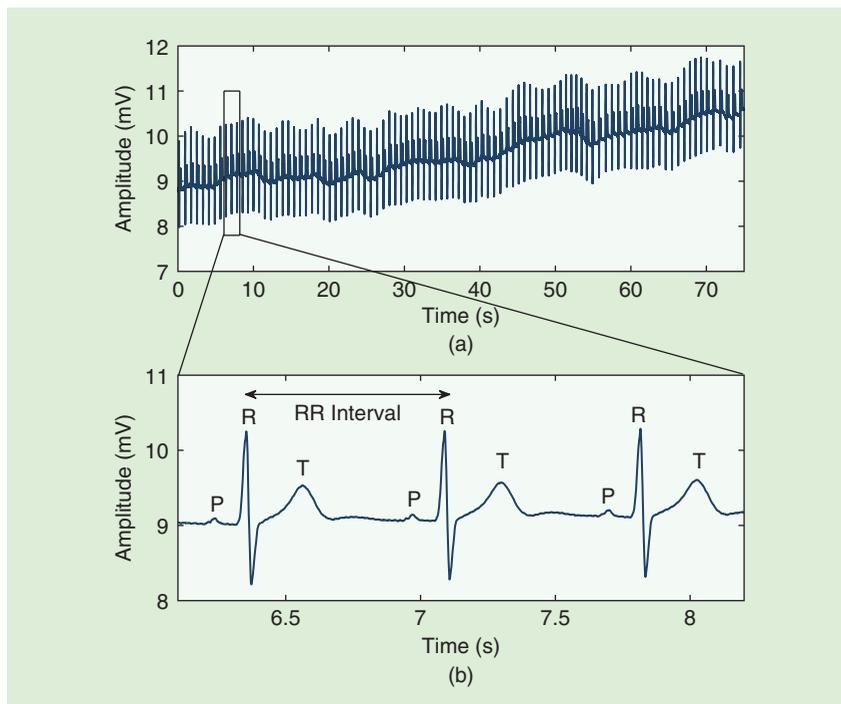


FIGURE 8. A student’s own real-world arm ECG recording of more than 75 s. (a) A typical raw ECG recording from iAmp that exhibits baseline drifts. (b) The magnified ECG plot with P-, R-, and T-waves.

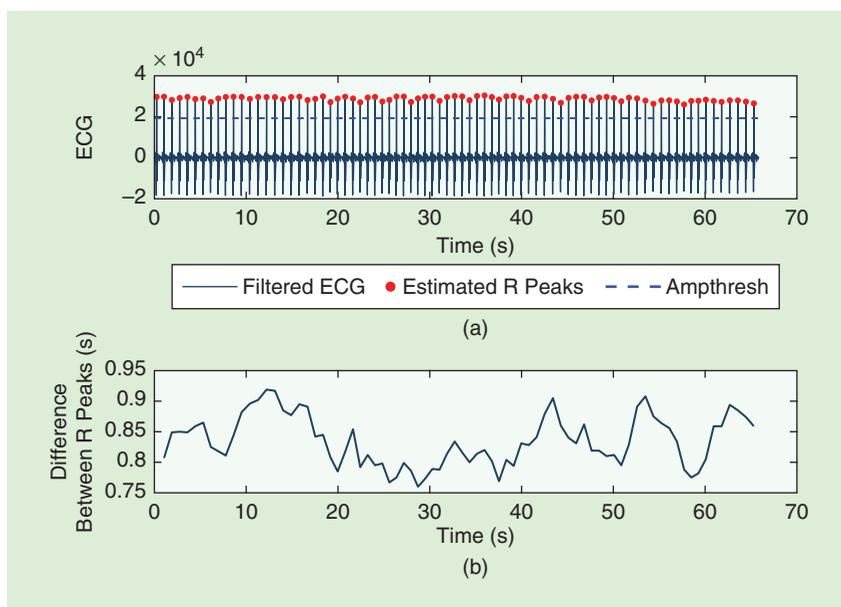


FIGURE 9. The detection of R-peaks in the ECG and the generation of HRV. (a) The band-passed filtered ECG and the suggested amplitude threshold (broken blue line). (b) The RRI obtained from the R-peak detection algorithm.

is generic, rather than considering real-world heart rates, and the exercise is of a theoretical nature.

To complement [12, Problem 2.4] with a hands-on practical example, we instructed the students to test the concepts of biased and unbiased estimators by deriving their own heart rates from their ECG recordings, as outlined in “Excerpt #1 from the Coursework Assignments” and Figure 7.

Another assignment involves extracting the breathing rates from the recorded ECGs, as respiration modulates ECG through respiratory sinus arrhythmia, as outlined in “Excerpt #2 from the Coursework Assignments” and illustrated in Figure 7(b). As mentioned previously, the first trial is a “baseline” experiment whereby students are allowed to breathe in an unrestricted fashion. The second and third trials, however, require the students to breathe at specific rates following metronome-like on-screen instructions. This gives the opportunity to extract the respiration rate from the ECG envelope using signal processing algorithms applied to the individual ECGs.

Student feedback

Over the academic years 2014–2015, 2015–2016, and 2016–2017, we analyzed student feedback from the Imperial College student online evaluation system (SOLE). Table 1 shows the number of students enrolled in our EE3-08 ASP course and the percentage of students who gave their feedback through SOLE. Figure 10 shows that the percentage of students who found the course to be intellectually stimulating (by checking the “Mostly Yes” and “Yes” boxes in the questionnaire) was above 80%, peaking at 85% in 2016–2017. It was our impression from 2015–2016 that, by providing MATLAB scripts for the preprocessing of raw ECG data, this somewhat decreased the incentive of some more adventurous students to apply their own preprocessing algorithms. This tradeoff between giving too many versus too few instructions is an ongoing challenge faced by educators. Figure 11 shows the statistics of student satisfaction with the module over the corresponding 2015–2017 period, with a similar trend as in

Excerpt #1 from the Coursework Assignments

Using your own RR-interval (RRI) signal $r[n]$ from Trial 1 (unconstrained breathing), obtain the heart rate $h[n]$ from

$$h[n] = \frac{60}{r[n]}. \quad (S1)$$

To obtain a smoother estimate of the heart rate, use the following method to average every ten samples of the heart rate:

$$\hat{h}[1] = \frac{1}{10} \sum_{i=1}^{10} \alpha h[i], \hat{h}[2] = \frac{1}{10} \sum_{i=11}^{20} \alpha h[i], \dots, \quad (S2)$$

where α is a scalar.

- Plot the probability density estimate (PDE) of the original heart rates $h[n]$ and the averaged heart rates $\hat{h}[n]$ for $\alpha = 1$ and $\alpha = 0.6$.
- Comment on the shape of the PDE of the averaged heart rates compared to the original heart rates. How does the constant α affect the PDE?

Excerpt #2 from the Coursework Assignments

Breathing at regular rates will make the presence of respiratory sinus arrhythmia in the cardiac (ECG) data more pronounced.

- Apply the standard periodogram as well as the averaged periodogram with different window lengths (e.g., 50 s and 150 s) to obtain the power spectral density (PSD) of the RR-interval (RRI) data. Plot the PSD of the RRI data obtained from the three trials separately.
- Comment on the differences between the PSD estimates of the RRI data from the three trials. Can you identify the peaks in the spectrum corresponding to frequencies of respiration (and their harmonics) for the three experiments?

Figure 10 and with more than 80% of students satisfied with the module.

Conclusions

We have explored ways to enrich some classic estimation theory topics by “signal processing for wearable health” aspects. The aim was to enable students to explore interdisciplinary signal processing challenges that are often encountered in their future jobs. This has also provided an opportunity to bring biopresence into the curriculum through the challenge of analyzing students’ own physiological data and to enhance their engagement through a de facto part-ownership of their course.

Overall, the students appreciated the experience of performing biosignal analysis on their own data and felt

Table 1. The number of students enrolled in the EE3-08 course and the percentage of those who gave their feedback online.

Year	2015	2016	2017
Number of students	98	80	78
Percentage who gave feedback	39%	54%	60%

that such a biopresence in the curriculum solidified the theoretical concepts taught in the class and in an enjoyable and engaging way. This approach further encourages the students to

- explore additional concepts not covered, or only partially so, during the lectures
- enhance their creativity both in learning and applying the concepts with the additional “opportunity

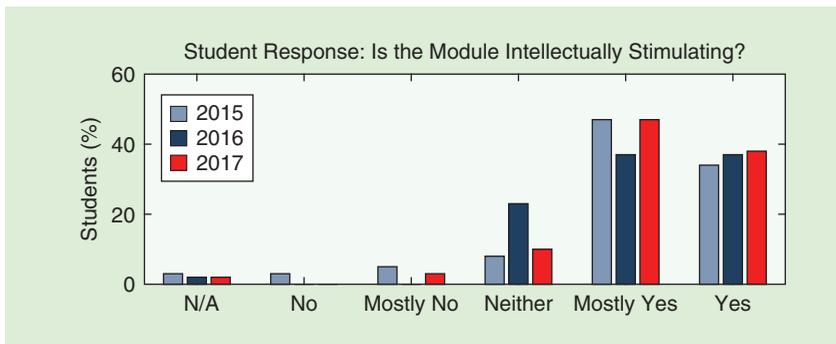


FIGURE 10. Feedback from students on whether the module was intellectually stimulating. More than 80% of students found that the assignments were engaging and intellectually stimulating.

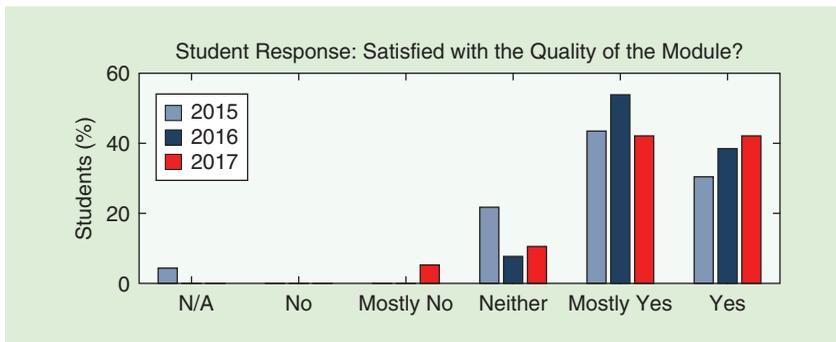


FIGURE 11. Feedback from students on their satisfaction with the module, with more than 80% of students satisfied.

windows” to explore possible product developments

- gain understanding about the need for medical ethics when working with human subjects
- experience that difficulties in experimentation and signal analysis are surmountable
- explore the cross-disciplinary, ethical, and social aspects of our work
- challenge themselves, engage their curiosity, and have the confidence to be intellectually adventurous.

We hope that we have shown that bringing research into the classroom is now not only feasible but a paradigm shift. This has also broadened the students’ perspective on research and employment opportunities, among other things, in next-generation health care [13]. Hopefully our readers, motivated by this article, will set out to further explore the ways of enriching the signal processing curriculum with relevant real-world examples of global importance, such as wearable health. To this end, our data acquisition platform includes our own

affordable, portable, and “hackable” bio-signal amplifier, the iAmp, a set of data acquisition, data format, and data transfer routines, and allows for the incorporation of other biosignal modalities (neural, movement) into future experiments.

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can be performed in the pole-zero form. The factored partial fraction expansion method has a very low computational complexity requirement, thus, it is ideal for cases when the conversion must be done on the fly. This comes at a price of a low-order FIR filter in series with the parallel sections.

The goal of this article is to raise awareness about the numerical issues related to the common way of converting filters to the parallel form, with the hope that the reader will find the alternative methods appealing and useful in many practical situations.

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Supplementary material

This article has supplementary downloadable material available at <http://ieeexplore.ieee.org>, provided by the

author. The material includes MATLAB functions required for converting IIR filters to parallel form and specific scripts to generate the example figures of the article. The files can also be downloaded at <http://www.mit.bme.hu/~bank/parconv>.

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