Refreshing DSP Courses through Biopresence in the Curriculum: A Successful Paradigm

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***Abstract*—Benefiting from the recent phenomenon that people and technology are becoming increasingly intertwined, we demonstrate that this also represents a paradigm–shift opportunity for Digital Signal Processing (DSP) educators to keep the curriculum current by syncing it to technological and educational developments. Our own first step in this direction was to bring research into the classroom, through bio–presence, which allowed us to center several classic DSP topics around the analysis of students' own physiological signals. This not only facilitates student engagement in curiosity-driven learning but also helps to broaden their perspective on next-generation health care, entrepreneurship, and to appreciate the relevance of their degree with respect to technological advancements. Case studies on the use of students' own Electroencephalogram (ECG) to illuminate both current and emerging DSP concepts support the approach, and include examples ranging from baseline drift removal (nonstationarity) to multiscale approaches and DSP for Big Data.**

***Index Terms*—DSP Education, biopresence in curriculum, students' vital signs, gadgets in classroom, research in classroom**

I. Introduction

The roots of Engineering education can be traced back to the 1770s, when the predecessor of today's Ecole Polytechnique started engaging in the education of artillery officers. This was followed by the establishment of the West Point military academy in the USA in 1802, with a similar aim. As much as these early promoters of Engineering education saw the opportunity to involve technology into the curriculum at that time. In fact, we now face a similar challenge – we are on the brink of a reform of Engineering education, in order to facilitate and promote a technology– and gadget–driven curriculum, within the emerging concept of Smart Classrooms.

Historically, the early Electrical and Electronics Engineering (EEE) departments grew out of Physics, however, the EEE discipline was not yet ready for the big challenges in the early 1940s. Indeed, most of the EEE-related work supporting WWII efforts (radar, sonar, code breaking, information theory) was performed by mathematicians and physicists. The advent of digital computers in the 1970s presented the opportunity for the development of our own Digital Signal Processing (DSP) discipline [1]–[3], while the EEE curriculum became too big and branched out into related degrees such as Bioengineering [4]. For most of the next 30 years the pendulum was firmly inclined towards Engineering Science, and a wide availability of personal computers in the 2000s helped to realise that this could facilitate a shift towards hands–on experience [5] [6].

Classic DSP courses were developed with e.g. communications and radar problems in mind [7]. While the basic material is still of fundamental importance and a backbone for current and future applications, we are faced with new challenges in presenting such material as:

- Students now approach new information and communication in a very different way from e.g. students 30 or 40 years ago;
- Hands–on experience, societal impact and entrepreneurship opportunities are becoming almost equally important as the core DSP taught material – one such example is the Equinox project by Imperial undergraduate students [8];
- The gadgets routinely used in our daily lives are a rich source of information and their use in the curriculum can trigger a paradigm shift in the way we approach modern education;
- The challenges that stem from the modern culture of *impatience and instant gratification*, together with the availability of computing power in mobile devices and personal computers, mean that the learning process should incorporate various forms of visualisation and "personalisation" of the taught material in order for students to absorb the material efficiently;
- Computing has been recognised to be a key analytical skill for engineers, and will inevitably have to become an integral part of the developments of the future technologically orientated classroom - the Smart Classroom.

In other words, we are on the verge of the next revolution in engineering education, which aims to refresh many classic and timeless maths–heavy modules across science and engineering, such as our own DSP discipline, with easy to understand and societally relevant hands–on experience [9] [10]. At the same time, this will help address the challenges related to societal changes in a fun and physically meaningful way, thus promoting student engagement and encouraging them to participate in curiosity driven learning. Our DSP discipline, being naturally close to the data acquired from various wearable sensors, is likely to play a pivotal role in this endeavour, as it serves both as an enabling technology for most wearable devices and their applications, and a mathematical lens into the physics behind the underlying signal generating mechanisms.

II. Biopresence in the Classroom: A Real Opportunity and a Paradigm Shift

In the academic years 2014–2015, 2015–2016 and 2016–2017, we investigated whether using wearable technology in the classroom would enrich students intellectual curiosity and engagement, and perhaps even performance, especially in maths-heavy DSP modules such as Estimation Theory. In a related research project on Hearables [11], we developed a miniature biosignal acquisition device – the iAmp shown in Fig. 1 (A) – that can measure up to eight channels of physiological data for 14 hours. An accompanying computer app gave onscreen instructions on how and when to gather data, in order to produce datasets of students' own heart and breathing rates via small electrodes on the wrist, as shown in Fig. 1 (B) [12]. For more information, please visit www.commsp.ee.ic.ac.uk/~mandic/Biopresence_Material.htm.

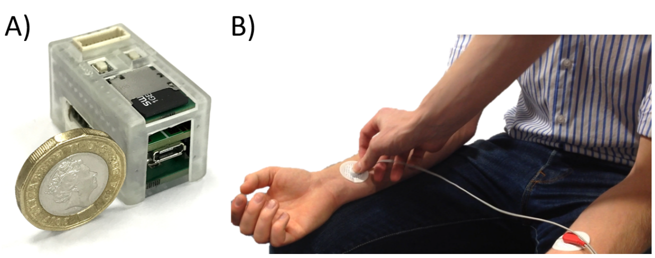

Fig. 1. A) Our iAmp biosignal recording device against one UK pound coin (22.5 mm in diameter). Data can be stored on an SD card or transported in real time to a computer via a mini USB port. B) Placement of electrodes on the forearms for the recording of ECG.

As part of the coursework, the students applied the taught mathematical concepts of signal estimation to their recorded vital signs and were graded as usual. The convenience and an over–arching nature of the approach taken in our DSP courses is self–evident from the real–life recorded ECG traces shown in Fig. 2. The students were asked to breathe according to different regimes of a metronome app on computer screen, which induced modulation into the ECG envelope and thus a multi–scale signal nature (visible in red on the top right corner), while the "wearable effects" on the recorded signal included various degrees and natures (deterministic, random) of baseline drifts (downwards, upwards, oscillatory), and artefacts (impulsive, effects of external electromagnetic fields). Overall, this bio–inspired approach offered a rich source of a real–world signal processing aspects, which are routinely covered in standard DSP courses, while benefiting from a convenient way for students to measure and physically interpret their own ECG.

III. Opportunities in a Smart Classroom through Physical Relevance of Taught Material

Baseline drift is the most common artefact in real–world recordings from electrodes and refers to a time–varying signal mean. This variation of mean can be piece–wise linear or assume any form of nonstationarity, as observed in Fig. 2 (B) for ECG recordings. Many other disciplines, such as finance, often have to deal with trends in data which typically exhibit similar properties to baseline drift; in both cases trend removal is the first step in the analysis. We next show that this issue in real–world recordings can serve as a rich resource for DSP education, as such a physically interpretable case study can be conveniently used when teaching a whole range of filtering

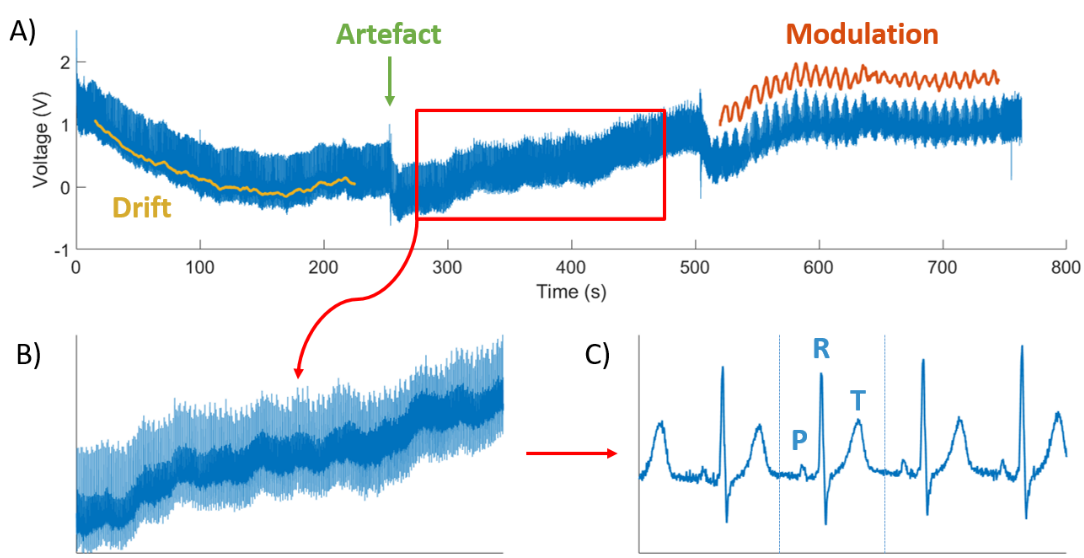

Fig. 2. An exemplar of a student's own ECG recording from the wrists. A) Three segments corresponding to different regimes of metronome-controlled breathing. Observe the different natures of trends (deterministic, random), impulsive artefacts, and the multiscale nature of respiration–modulated ECG (Modulation, in red). B) A zoom-in into the middle segment of data. C) The clean ECG after the student applied several DSP concepts to the raw data in A). Observe the very clean R– and T–waves in ECG after digital filtering.

techniques, from moving average (MA) FIR filters through to Kalman filters [13].

We next demonstrate the virtues of the proposed approach through concrete practical examples in teaching:

1) Digital filter design for baseline drift removal
2) Numerical differentiation and integration
3) Tensor decompositions for big data applications

A. Digital filter design for baseline drift removal

Consider an MA filter which averages input data over N samples, given by

$$y[n] = \frac{x[n] + x[n-1] + \cdots + x[n-N-1]}{N} \tag{1}$$

for which the frequency response is given in Fig. 3. Clearly, an appropriate choice of data segment N would yield a good estimate of time–varying signal mean. Fig. 4 shows the estimates of baseline drift using least-squares linear regression (LR) and the MA filter in Eq. (1) with a window of 2 seconds ($N = 2000$). Observe that the MA filter was able to mitigate the effects of drift, while also serving as a fertile ground for students to experience the effects of parameter tuning, data window length and the corresponding frequency responses.

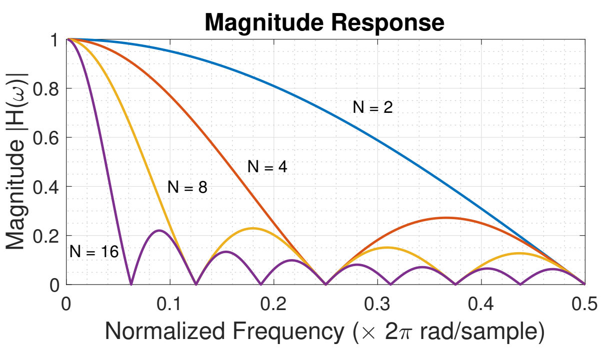

Fig. 3. Frequency response of the MA filter in (1).

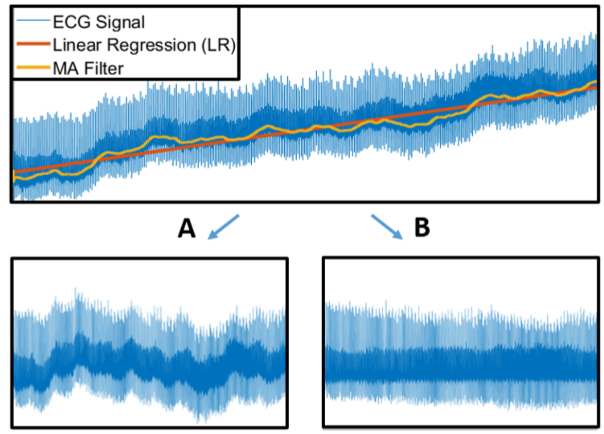

Fig. 4. Baseline drift removal from ECG using linear regression (LR) and a moving average (MA) filter in (1). Observe both the "deterministic" (straight line) and "stochastic" (random local oscillations) component in ECG drift in the top panel. A) Drift removal using LR. B) Drift removal using the MA filter.

B. Numerical methods

Numerical differentiation and integration are at the very core of DSP education. The ECG is perfectly suited to demonstrate the imperfections of numerical methods, as it contains both low frequency components (P-, Q-, S- and T- waves), high frequency components (sharp R-peaks), and broadband recording noise. Fig. 5 (A) and (B) show respectively an ECG signal and its numerical derivative, obtained through the simplest $x[n] - x[n-1]$ approximation. Students can immediately observe that even this crudest derivative has the desired effect of removing low–frequency components (the T–wave) but also comes with a drawback of amplifying high frequency noise. In the next step, after applying 'leaky' numerical integration through an MA filter (as in Eq. (1), with $N = 10$), the high frequency noise becomes suppressed, as desired, so that the R–waves become more prominent but the information in the the low–frequency T–waves is irretrievably lost, as shown in Fig. 5 (C). This example can be straightforwardly extended to cover the effects of sampling frequency, and to explore other numerical derivatives and integrators.

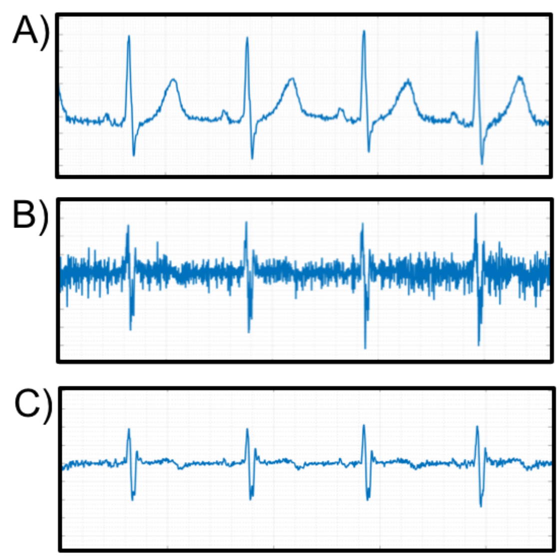

Fig. 5. The effects on ECG of numerical differentiation followed by numerical integration. A) Original ECG signal. B) Numerical derivative of ECG in A) using first order time difference $x(n) - x(n-1)$. C) Signal in B after numerical integration using MA filtering.

C. Signal processing for big data

Multidimensional arrays (or tensors) are common in the analysis of big data, but despite their enormous practical usefulness it is still rare to cover tensors within the DSP curriculum. This is largely because it is difficult to find easy to digest and intuitive examples which would demonstrate the power of tensor algebra. We next provide such an illuminating example based on students' own ECG, our own recent developments in tensor visualisation [14] [15] and our open source software package HOTTBOX [16]. Although 5–10 minutes of ECG does not qualify as big data source per se, we first show that methods of tensorisation introduce redundancy and thus enlarge dimensionality in data, which then admits the use of subsequent tensor factorisations to extract physically meaningful information. Fig. 6 illustrates the construction of a third order tensor from the vector of ECG, constructed by taking the short-time Fourier transform (STFT) of the Hankel-folded first order derivative of the ECG. The one–factor Canonical Polyadic Decomposition (CPD) was then applied which extracted the fundamental frequency of heart rate, modulated by respiration in its envelope (see also Fig. 2, top right panel). In this way, students also experience direct exposure to high–dimensional alternatives to Principal Component Analysis (PCA).

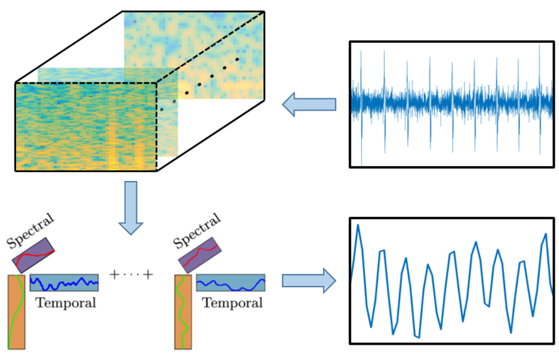

Fig. 6. Using "bio–presence" to teach tensor decompositions for Big Data analytics, an example where Canonical Polyadic Decomposition (CPD) reveals the fundamental periodic pattern in ECG. *Counterclockwise from top right:* First order derivative of the ECG; Data tensor formed by Hankel–folding and STFT; Principle of tensor factorisation using CPD; Fundamental periods in data identified in factor–one CPD (heart rate modulated by respiration).

IV. Conclusion

We have illuminated some of the opportunities in next–generation DSP education that arise through the use of wearable sensing in the classroom. This approach has been shown to not only bridge the gap between the mathematics–heavy DSP backbone and its practical applications, but also to serve as a vehicle to modernise current DSP curricula and provide enhanced physical insight into the taught material. The so enabled framework for the unification of multiple aspects of DSP curriculum under the umbrella of "bio–presence", established through processing of students' own vital signs, has also been demonstrated to permit seamless migration of ideas from standard DSP curriculum to curiosity driven learning, and vice versa, together with an open platform for further developments. It is our hope that this "participatory approach" to DSP education will both demystify the role of DSP as a mathematical lens into the real world and further empower educators and students with enhanced intuition and freedom in algorithmic design.

It could not be more appropriate but to conclude with:

> "The roots of education are bitter, but the fruit is sweet". Aristotle 384–322 BC

Epilogue

More than 85% out of the 450 students involved described increased intellectual satisfaction and engagement with the overall approach. They expressed their appreciation for the opportunity to enhance their creativity by exploring additional concepts not covered, or only partially so, during the lectures, together with the experience that difficulties in experimentation and signal analysis are surmountable.

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References

[1] A. G. Constantinides, "Spectral transformations for digital filters," *Proceedings of IEE*, vol. 117, no. 8, pp. 1585–1590, 1970.

[2] A. Buttle; A. G. Constantinides; J. E. Brignell, "Online digital filtering", *In Electronics Letters*, vol. 4, no. 12, pp. 252-253, 1968

[3] F. J. Harris, "On the use of windows for harmonic analysis with the discrete Fourier transform," *In Proceedings of the IEEE*, vol. 66, no. 1, pp. 51–83, 1978.

[4] A. Bashashati, M. Fatourechi, R. K. Ward, and G. E. Birch, "A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals," *Journal of Neural Engineering*, vol. 4, no. 2, pp. 32–57, 2007.

[5] G. C. Orsak and D. M. Etter, "Collaborative SP education using the internet and MATLAB," *IEEE Signal Processing Magazine*, vol. 12, no. 6, pp. 23–32, 1995.

[6] T. B. Welch, D. M. Etter, C. H. G. Wright, M. G. Morrow, and G. J. Twohig, "Experiencing DSP hardware prior to a DSP course," *In Proceedings 10th IEEE Digital Signal Processing Workshop*, pp. 297–301, 2002.

[7] C. H. G. Wright, T. B. Welch, D. M. Etter, and M. G. Morrow, "A systematic model for teaching DSP," *In Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 4, pp. 4140–4143, 2002.

[8] "e.quinox," http://wwwf.imperial.ac.uk/blog/equinox/

[9] E. Richter and A. Nehorai, "Enriching the undergraduate program with research projects," *IEEE Signal Processing Magazine*, vol. 33, no. 6, pp. 123–127, 2016.

[10] A. V. Oppenheim, "One plus one could equal three (and other favorite cliches)," *IEEE Signal Processing Magazine*, vol. 23, no. 6, pp. 10–12, 2006.

[11] V. Goverdovsky, W. von Rosenberg, T. Nakamura, D. Looney, D. J. Sharp, C. Papavassiliou, M. J. Morrell, and D. P. Mandic, "Hearables: Multimodal physiological in-ear sensing," *Nature Scientific Reports*, vol. 7, article 6948, pp. 1-10, 2017.

[12] S. Kanna, W. von Rosenberg, V. Goverdovsky, A. G. Constantinides, and D. P. Mandic, "Bringing wearable sensors into the classroom: A participatory approach," *IEEE Signal Processing Magazine*, vol. 35, no. 3, pp. 110–130, 2018.

[13] D. P. Mandic, S. Kanna, and A. G. Constantinides, "On the intrinsic relationship between the least mean square and Kalman filters," *IEEE Signal Processing Magazine*, vol. 32, no. 6, pp. 117–122, Nov 2015.

[14] A. Cichocki, N. Lee, I. Oseledets, A. Phan, Q. Zhao, and D. P. Mandic, "Tensor networks for dimensionality reduction and large-scale optimization. Part 1: Low-rank tensor decompositions," *Foundations and Trends in Machine Learning*, vol. 9, no. 4-5, pp. 249–429, 2016.

[15] A. Cichocki, A. Phan, Q. Zhao, N. Lee, I. Oseledets, M. Sugiyama, and D. P. Mandic, "Tensor networks for dimensionality reduction and large-scale optimization. Part 2: Applications and future perspectives," *Foundations and Trends in Machine Learning*, vol. 9, no. 6, pp. 431–673, 2017.

[16] I. Kisil, A. Moniri, G. G. Calvi, B. Scalzo Dees, and D. P. Mandic, "HOTTBOX: Higher Order Tensor ToolBOX," https://github.com/hottbox