Ultra low power signal processing in mHealth: Opportunities and challenges

Alexander J. Casson, *Member, IEEE*

***Abstract*— This mini-symposium talk will overview the state-of-the-art in wearable algorithms: the new signal processing approaches that are emerging for wearable devices which embed signal processing into the device hardware. They can be used to increase functionality and enable closed-loop recording–stimulation with minimal latency, amongst other benefits.**

I. OVERVIEW

Wearable devices are starting to revolutionize healthcare and mobile healthcare by allowing the easy, unobtrusive and long term monitoring of a range of body parameters. Activity trackers using accelerometers, such as the fitbit [1], have been the most successful initial devices. There is now a major opportunity to monitor more physiological parameters using wearables. For example, new devices such as the Samsung Simband [2] can monitor a range of parameters including activity, arousals, and heart rate. Wearable algorithms are the new signal processing approaches that are emerging for wearables which embed signal processing into the device hardware itself [3]. Illustrated in Fig. 1, historically the focus of online signal processing in sensor nodes has been real-time data reduction [4]. Today, there are many additional benefits to be realized by the use of signal processing embedded in the hardware [3]:

- Reduced system power consumption.
- Increased device functionality.
- Reliable, robust operation over unreliable wireless links.
- Minimized system latency.
- Reduction in the amount of data to be analysed offline.
- New closed-loop recording–stimulation devices.
- Better quality recordings (e.g. with artefact removal).
- Real-time data redaction for privacy.

Using a new review, summarized in Table I, and examples from a case study on wearable algorithms for EEG, this mini-symposium talk will overview the 2015 state-of-the-art in wearable algorithms. It will highlight the truly multi-disciplinary approaches required, spanning: human-monitoring application design; signal-processing design; performance-testing design; and circuit design. It will demonstrate how the interactions between these different domains can be used to improve performance.

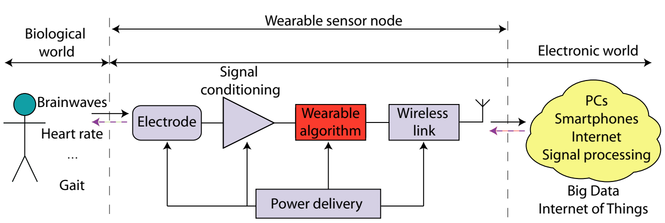

Fig. 1. Wearable algorithms can be used to enable a range of benefits to wearable devices, if they operate with sufficiently low power consumption.

This work was supported by the Engineering and Physical Sciences Research Council grant number EP/M009262/1. A. J. Casson is with the School of Electrical and Electronic Engineering, The University of Manchester, UK. Email: alex.casson@manchester.ac.uk.

TABLE I
2014 AND 2015 WEARABLE ALGORITHMS. SENSITIVITY (SEN), SELECTIVTY (SEL), DATA COMPRESSION (C), PERFORMANCE (PERF.).

Ref.	Aim	Algorithm perf.	Power perf.
[5]	ECG heart beat detection	Sen: 97.8%, Sel: 98.6%	220 nW
[6]	ECG heart beat detection	Sen: 99.3%	435 nW
[7]	ECG compression	C: x2.3	2.14 μW
[8]	ECG artefact removal and heart beat detection	Sel: 99.8%	43 μW
[9]	ECG heart beat detection and compression	Sen: 99.6%, Sel: 99.8%, C: x2.3	490 nW
[10]	ECG heart beat detection and compression	Sen: 99.7%, Sel: 99.5%, C: x13.7	33 μW
[11]	Apnoea detection	Sen: 100%, Sel: 85.9%	33 μW
[12]	EEG seizure detection	F1 score: 91%	37 nW

REFERENCES

[1] fitbit. (2014) Home page. [Online]. Available: http://www.fitbit.com/

[2] Simband. (2015) Home page. [Online]. Available: http://www.voiceofthebody.io/

[3] G. Chen, *et al.*, "Wearable algorithms: An overview of a truly multi-disciplinary problem," in *Wearable sensors*, E. Sazonov and M. R. Neuman, Eds., Amsterdam: Elsevier, 2014, pp. 353–382.

[4] S. A. Imtiaz, *et al.*, "Compression in wearable sensor nodes: Impacts of node topology," *IEEE T-BME*, vol. 61, no. 4, pp. 1080–1090, 2014.

[5] X. Zhang, *et al.*, "A 300-mV 220-nW event-driven ADC with real-time QRS detection for wearable ECG sensors," *IEEE T-BioCAS*, vol. 8, no. 6, pp. 834–843, 2014.

[6] X. Liu, *et al.*, "A 457 nW near-threshold cognitive multi-functional ECG processor for long-term cardiac monitoring," *IEEE JSSC*, vol. 49, no. 11, pp. 2422–2434, 2014.

[7] C. J. Deepu, *et al.*, "An ECG-on-chip with 535 nW/channel integrated lossless data compressor for wireless sensors," *IEEE JSSC*, vol. 49, no. 11, pp. 2435–2448, 2014.

[8] H. Kim, *et al.*, "A configurable and low-power mixed signal SoC for portable ECG monitoring applications," *IEEE T-BioCAS*, vol. 8, no. 2, pp. 257–267, 2014.

[9] C. J. Deepu, *et al.*, "A joint QRS detection and data compression scheme for wearable sensors," *IEEE T-BME*, vol. 62, no. 1, pp. 165–175, 2015.

[10] Y. Zou, *et al.*, "An energy-efficient design for ECG recording and R-peak detection based on wavelet transform," *IEEE T-CAS II*, vol. 62, no. 2, pp. 116–123, 2015.

[11] J. Jin, *et al.*, "A home sleep apnea screening device with time-domain signal processing and autonomous scoring capability," *IEEE T-BioCAS*, vol. 9, no. 1, pp. 96–104, 2015.

[12] A. Page, *et al.*, "A flexible multichannel EEG feature extractor and classifier for seizure detection," *IEEE T-CAS II*, vol. 62, no. 2, pp. 109–113, 2015.