OPPORTUNITIES AND CHALLENGES FOR ULTRA LOW POWER SIGNAL PROCESSING IN WEARABLE HEALTHCARE

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ABSTRACT

Wearable devices are starting to revolutionise healthcare by allowing the unobtrusive and long term monitoring of a range of body parameters. Embedding more advanced signal processing algorithms into the wearable itself can: reduce system power consumption; increase device functionality; and enable closed-loop recording–stimulation with minimal latency; amongst other benefits. The design challenge is in realising algorithms within the very limited power budgets available. *Wearable algorithms* are now emerging to answer this challenge. Using a new review, and examples from a case study on EEG analysis, this article overviews the state-of-the-art in wearable algorithms. It demonstrates the opportunities and challenges, highlighting the open challenge of performance assessment and measuring variability.

***Index Terms*—** Wearables, power, performance metrics

1. INTRODUCTION

Wearable devices are starting to revolutionise 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, and emerging units, such as the Samsung Simband [2], can monitor a range of parameters including accelerometry for activity monitoring, electrodermal activity for arousals, and heart rate via photoplethysomgraphy. *Wearable algorithms* is the name given to the new signal processing approaches that are emerging for wearable devices which embed signal processing into the device hardware [3]. Illustrated in Fig. 1, historically the focus of online signal processing inside a sensor node has been for real-time data reduction. In wireless sensors it is the transmitter that dominates power consumption and if the data rate can be reduced prior to transmission significantly better battery life can be achieved [4]. Today, there are many additional benefits that are being enabled by the use of signal processing embedded in the wearable itself [3]:

- Reduced system power consumption.

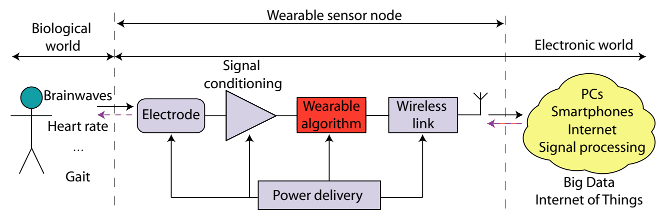

Fig. 1. Low power *wearable algorithms* can be used to enable a range of benefits to wearable devices.

- 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 records (e.g. with motion artefact removal).
- Real-time data redaction for privacy.

As a result there have been rapid developments in wearable algorithms in recent years, and this is opening new opportunities in signal processing techniques, algorithms, and applications for delivering healthcare benefits. Using a new review, and examples from a case study on EEG analysis, this article overviews the 2015 state-of-the-art in wearable algorithms (Section 2). These then highlight (Section 3) the gaps in the research landscape that are emerging, and the corresponding opportunities and challenges.

2. WEARABLE ALGORITHMS

Wearable algorithms is a new discipline in signal processing distinguished by the requirements for very low power hardware implementations *and* power consumption aware performance testing [3]. This was a key driver in the development of compressive sensing as a major signal processing area as it provides low power consumption compression with little distortion [4]. Nevertheless, the underlying aim of compressive sensing is data reduction for reduced power consumption. It does not enable the other potential benefits of wearable algorithms highlighted in the introduction. To do this, specif-

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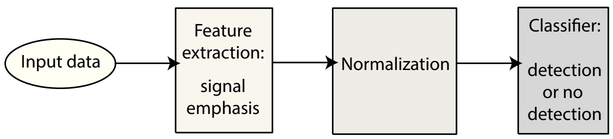

Fig. 2. Principal stages of a wearable algorithm.

ically designed algorithms for each application are required. Although there are open challenges in each stage, the general flow for these algorithms is shown in Fig. 2. The key stages are low power feature extraction and low power classification. To investigate the state-of-the-art in these blocks Table 1 presents a new review of papers published in IEEE Transactions since 2011 that implement some form of algorithm in hardware for use in wearable sensors. Our focus is on full hardware implementations for the lowest power consumption, rather than software implementations with some hardware accelerators. Table 1 thus provides key insights into the main approaches that are currently being used in algorithms for wearables, and the current state-of-the-art.

3. GAPS IN THE SIGNAL PROCESSING LANDSCAPE

Focusing on power consumption, in 2010 authors in the IEEE Signal Processing magazine discussed the question: What does ultra low power consumption mean? They came to the conclusion that it is where the "*power source lasts longer than the useful life of the product*" [25]. To operate for 10 years from a miniature 1000 mAh battery, the average current draw needs to be approximately 10 μA or less. The largest current draw in Table 1 is $\sim$170 μA, and there are a number of algorithms that are in the $<$10 μA range, making this goal close to being realised. Such low power levels are possible due to the low frequency nature of human physiology. Few parameters need to be sampled at more than 1 kHz and this allows the signal processing electronics to be heavily duty cycled or power scaled. As a case study, Fig. 3 shows a Continuous Wavelet Transform (CWT) circuit which is designed for processing brainwave (EEG) signals in the 2 Hz region. This low frequency allows the average current draw to be scaled to 60 pA, giving signal processing information essentially *for free* in terms of power consumption. As a result the most substantial opportunities and challenges for wearable algorithms lie in the interface with algorithmic approaches as opposed to in pure circuit design.

Focusing on feature extractions, the majority of wearable algorithms created so far (12 out of the 20 in Table 1) are based upon frequency information, with wavelet transforms being particularly popular. Given the results in Fig. 3 this focus is not surprising as it leads to very low power consumptions. However, it indicates a potential over reliance on time–frequency decompositions as the best algorithmic starting point. It seems unlikely that wavelet decompositions

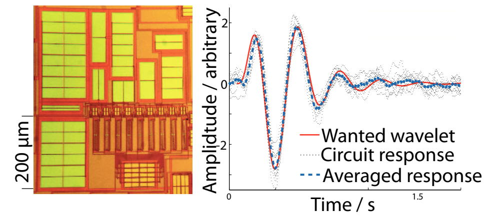

Fig. 3. Microphotograph and operation of a low frequency, 60 pW, CWT for real-time EEG analysis [7].

would provide the best, or even suitable, feature extraction across all signal types and all potential applications. There is a clear opportunity for creating wearable algorithms that are based on other feature extraction methods, such as the fractal dimension [26] or Empirical Mode Decomposition [27]. Similarly focusing on classifiers, while there has been recent work on low power implementations of Support Vector Machines (SVMs) (e.g. [15]), many current wearable algorithms are based on threshold detection. The wide range of machine learning approaches have not yet been explored. Recent results [28] have suggested that many disparate classifiers actually achieve very similar algorithm performance. If confirmed this is an ideal opportunity for wearable algorithms. It means the classification procedure can be selected for minimum power consumption, with little impact on the classification accuracy.

Investigating this requires studying the three-way tradeoff between algorithm *performance* (e.g. correct detections), algorithm *cost* (e.g. false detections), and *power consumption*. This is a large design space, which leads to difficult decisions for the system designer: is it preferable to maximize *performance*, or to minimize *cost* or to minimize *power consumption*? Is an algorithm with very low power consumption, but comparatively low algorithm performance a better choice than a higher power, higher performance algorithm? Fully, and systematically, exploring this design space is the major challenge facing wearable algorithms. The algorithms in Table 1 are beginning to populate the space, but there is much more to do. It is an open challenge to formally investigate the trade-offs present (as opposed to making individual algorithms and finding where they lie) which could lead to more automated tools for helping designers choose the most appropriate trade-off point for their application.

The above challenge is compounded by the difficulties in assessing algorithm *performance* and *cost* in healthcare applications. Many applications in healthcare are highly variable between different people, and within the same person over time. For example, recent compressive sensing results have highlighted that the level of algorithm success is dominated by the variance in performance over time, not the average performance level [4, 29]. Similarly, Fig. 4 shows the algorithm performance results of a CWT based spike detection method when multiple records are analysed [30]. Ideal performance would be in the top left hand corner. Performance

Table 1. Performance of state-of-the-art wearable algorithms: algorithm performance and power performance.

Ref.	Aim	Features	Classifier	Algorithm performance	Power performance
[5]	ECG adaptive sampling frequency	Frequency information (Bandpass filter)	Multiple thresholds	x7 data compression	30 μW, 2 V
[6]	EEG band power extraction	Frequency information (Bandpass filter)	–	–	3 μW, 1.2 V
[7]	EEG band power extraction	Frequency information (CWT)	–	–	60 pW, 1 V
[8]	ECG heart beat detection	Frequency information (DWT)	Multiple thresholds	99.8% sensitivity, 99.9% selectivity	29 μW, 1 V
[9]	Signal agnostic compression (EEG, ECG, optical)	Lossless compression (discrete pulse code modulation)		x2 data compression	170 μW, 1 V
[10]	ECG artefact removal	Time domain electrical impedance tomography	LMS adaptive filter	10 dB increase in Signal-to-Artefact power	–
[11]	ECG heart beat detection	Frequency information (DWT)	Maximum-likelihood	–	0.88 pJ/sample, 0.32 V
[12]	EEG application agnostic compression	Compressive sensing		10 dB SNDR, x10 data compression	2 μW, 0.6 V
[13]	ECG heart beat detection	Frequency information (DWT)	Multiple thresholds	99.3% sensitivity, 99.7% selectivity	0.8 μW, 1.8 V
[14]	ECG heart beat detection	Frequency information (DWT)	Maximum-likelihood	Error rate 0.2%	14 μW, 3 V
[15]	EEG seizure detection EEG blink detection	Frequency information (FIR filter)	SVM	83% detection rate, 4.5% false 84% detection rate	2 μJ/classification, 1 V 128 classifications/s
[16]	ECG heart beat detection	Frequency information (DWT)	Multiple thresholds	99% sensitivity, 99% selectivity	3 μW
[17]	ECG heart beat detection	Analogue-to-information converter		97.8% sensitivity, 98.6% selectivity	220 nW, 0.3 V
[18]	ECG heart beat detection	Frequency information (DWT)	Multiple thresholds	99.3% sensitivity	435 nW, 0.5 V
[19]	ECG application agnostic compression	Lossless compression (slope based linear predictor)		x2.3 data compression	2.14 μW, 2 V
[20]	ECG artefact removal and heart beat detection	Adaptive filtering and frequency information (CWT)	Multiple thresholds	99.8% selectivity	43 μW, 1.2 V
[21]	ECG compression and heart beat detection	Slope based linear predictor	Multiple thresholds	99.6% sensitivity, 99.8% selectivity, x2.3 data compression	490 nW, 1.8 V
[22]	ECG compression and heart beat detection	Frequency information (DWT)	Multiple thresholds	99.7% sensitivity, 99.5% selectivity, x13.7 data compression	33 μW, 0.7 V
[23]	Apnoea detection from pressure sensor	Time domain amplitude and duration	Multiple thresholds	100% sensitivity, 85.9% selectivity	33 μW, 5 V
[24]	EEG seizure detection	Time domain signal measures	Logistic regression	91% F1 score	37 nW, 1 V

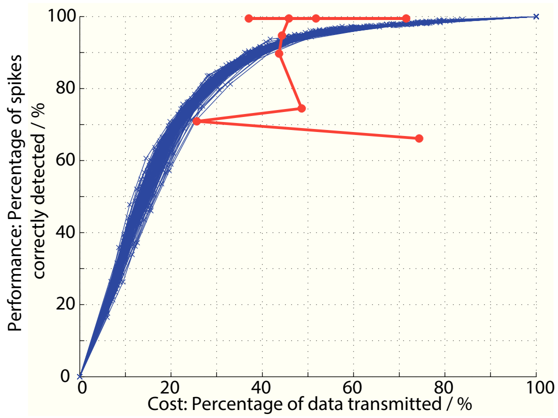

Fig. 4. Performance variances. Red: across inter- and intra-subject records [30]; Blue: due to circuit non-idealarities.

results in different records (red lines) show the common pattern of: many records have high *performance* and acceptably low *cost*; some records have high *performance*, but too high *cost*; and a few records have both *performance* and *cost* too poor. Overlaid (blue lines) is the variance in the average performance introduced due to the non-ideal CWT of Fig. 3 being used. The variance in performance between records is much larger than the variance introduced due to the non-ideal, and very low power, circuit implementation. As a result there is potential for designing even lower power algorithms with more variance, without substantially impacting the average algorithm performance. However, just as early wearable algorithms often did not report measures of both algorithm and power performance [3], many current wearable algorithm approaches report only an average performance level. There is no assessment of intra- and inter- person variability. This is because there is a substantial challenge in devising new methods for accurately and compactly summarising and reporting algorithm variances which can be compared between approaches. This is essential for algorithms to be usable in clinical grade healthcare applications (as opposed to consumer grade applications) and to accelerate the creation of future wearable algorithms. Unfortunately at present there are few methodological tools avaiable, and little consensus for how to best measure and quantify this variability.

Finally, Fig. 5 shows the average performance of the CWT based algorithm from Fig. 4 as the amount of input noise is increased. Traditional design approaches always endeavour to minimize the effective noise present in a system, often by trading-off with increased power consumption. However, noise-enhanced algorithms are a branch of signal processing theory where algorithm performance is not only robust in the presence of noise, but up to a certain point it gets better as more noise is introduced [31]. Noise-enhancement is therefore of great interest for simultaneously reducing power consumption and improving signal processing performance in low power wearables. While compressive sensing is the best

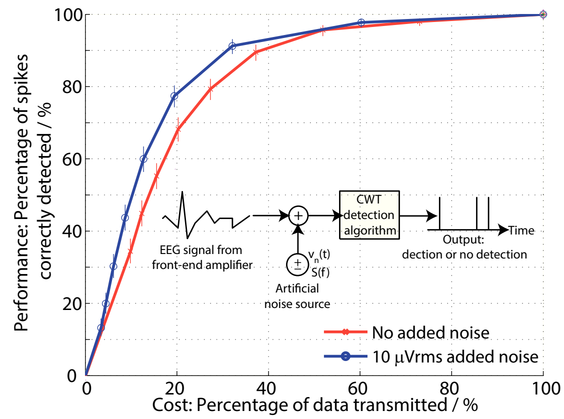

Fig. 5. CWT algorithm [30] gets better average performance with small amounts of extra noise deliberately added in.

known recent development in signal processing theory applicable to wearable algorithms, there are undoubtedly major opportunities for the greater use of noise-enhancement, and also in using innovations from other branches of signal processing theory which have not yet been identified.

4. CONCLUSIONS

Wearable algorithms are an emerging truly multi-disciplinary problem where, to achieve better functionality at the lowest levels of power consumption, innovations are required on multiple levels: in the human-monitoring application design, in the signal-processing design, in the performance-testing design and in the circuit design. This presents a large, four-dimensional, multi-disciplinary design space that has not yet been fully explored by a long way. Many challenges and opportunities are present, and while innovative design at all of the four levels in isolation will be beneficial, for future systems it is critical to exploit the multi-disciplinary factors present and the interactions between the different levels.

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