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Signal agnostic compressive sensing for Body Area Networks: Comparison of signal reconstructions

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Abstract— **Compressive sensing is a lossy compression technique that is potentially very suitable for use in power constrained sensor nodes and Body Area Networks as the compression process has a low computational complexity. This paper investigates the reconstruction performance of compressive sensing when applied to EEG, ECG, EOG and EMG signals; establishing the performance of a signal agnostic compressive sensing strategy that could be used in a Body Area Network monitoring all of these. The results demonstrate that the EEG, ECG and EOG can all be reconstructed satisfactorily, although large inter- and intra- subject variations are present. EMG signals are not well reconstructed. Compressive sensing may therefore also find use as a novel method for the identification of EMG artefacts in other electro-physiological signals.**

I. INTRODUCTION

There are a number of electro-physiological signals associated with the normal and abnormal operation of the human body: the EEG (electroencephalogram) records signals from the brain; the ECG (electrocardiogram) signals from the heart; the EOG (electrooculogram) signals from the eyes; and the EMG (electromyogram) signals from muscles. Body Area Networks aim to monitor these using lightweight, easy-to-use and long lasting wearable sensors to facilitate improved diagnosis and treatment, and a shift towards personalised and preventative healthcare [1]. For long term autonomous operation from the physically smallest batteries, power consumption is a critical design factor. It is now widely accepted that the sensor power consumption can be reduced by the inclusion of real-time data compression embedded within the sensor itself [2], [3]. The challenge lies in having compression algorithms that provide a high level of data reduction while introducing little error into the recorded signal and requiring very little power to operate.

Compressive sensing [4], [5] is a recent lossy compression technique which is potentially very suitable for use within this aim [6]. The fundamental compression step is a random sampling of the input signal and has a very low computational complexity for running online/in real-time on the power constrained sensor. This low computational complexity is traded-off with having a higher complexity when the input signal is reconstructed from the compressed samples. However, this reconstruction is done on a smart-phone or fixed computer, which have much larger power budgets than the sensor node. Due to this beneficial arrangement, hardware implementations of compressive sensing sensor nodes for physiological signals are starting to emerge. [7] presented an ECG compressive sensing node based upon Texas Instruments' popular MSP430 micro-controller. [8] presented a fully custom compressive sensing micro-chip, testing its operation using invasively recorded EEG signals.

The underlying theory of compressive sensing has been established previously [4], [5], however its practical application performance is still under investigation. As a lossy compression scheme there is an inevitable trade-off between the amount of data compression provided and the amount of error introduced into the reconstructed signal. The error depends on two critical factors:

1) The measurement matrix $\mathbf{\Phi}$ and reconstruction basis $\mathbf{\Psi}$ must be incoherent. (See Section II for definitions.)
2) The input signal $\mathbf{x}$ must be sparse in the basis $\mathbf{\Psi}$. (For $\mathbf{x} = \mathbf{\Psi s}$ the majority of entries in $\mathbf{s}$ should be ~ 0.)

Condition one can be satisfied by choosing entries in $\mathbf{\Phi}$ from a random distribution [5]. Condition two can be much more challenging to satisfy. Generally $\mathbf{\Psi}$ is chosen on a signal-by-signal basis and the reconstruction process is not signal agnostic. There have therefore been a number of assessments of the reconstruction performance for different applications [9]–[12]. However considering each signal in isolation makes it impossible to test the validity of the signal-by-signal $\mathbf{\Psi}$ requirement and to asses its impact on performance. It is also not possible to establish the cross-signal performance of the underlying compressive sensing.

This paper investigates the use of one compressive sensing scheme on different physiological signals to investigate both of these effects. The same compressive sensing method, described in Section II, is used to compress and reconstruct EEG, ECG, EOG, and EMG signals recorded from the surface of the body. All of these have their own time and frequency domain properties, but are electro-physiological in nature, differing most in principle by the place on the body they are recorded from. They therefore provide the ideal inputs for assessing the relative performance of compressive sensing on similar yet different signals. The results in Section III thus provide a direct comparison of compressive sensing for these different signals. This is of particular relevance to the use of compressive sensing in Body Area Network applications where all of these would intrinsically be recorded simultaneously. The results establish the baseline level of cross-signal performance to be expected in such applications and suggest a new use for compressive sensing in muscle artefact identification.

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II. METHODS

The compressive sensing scheme used in this work is described in Section II-A. Its performance is assessed by taking pre-recorded electro-physiologic signals and using MATLAB to decompose and reconstruct them. The difference between the original and reconstructed signals is then assessed as differing levels of compression are provided. Four different input signals, described in Section II-B, are used to test the one compressive sensing scheme, simulating the use of compressive sensing in a Body Area Network controller where there are multiple compressively sensed signals arriving to be recovered using the same reconstruction algorithm. The performance metrics used are given in Section II-C.

A. Compressive sensing scheme

For each input signal $\mathbf{x}$—here an EEG/ECG/EOG/EMG channel recorded by placing electrodes on the skin—a compressively sensed representation is generated in the digital domain by carrying out the matrix multiplication

$$\mathbf{y} = \mathbf{\Phi x}. \tag{1}$$

Here $\mathbf{x}$ is a non-overlapping frame of N samples, and $\mathbf{\Phi}$ is an $M \times N$ sensing matrix. Thus if $M < N$ data compression is achieved in $\mathbf{y}$, with compression ratio $CR = \frac{M}{N}$.

It is this vector $\mathbf{y}$ that is actually passed from the sensor node to the smart-phone/analysis computer. Reconstruction of $\mathbf{x}$ from $\mathbf{y}$ is possible, even if $\mathbf{y}$ has fewer samples than a signal sampled at the Nyquist rate, by solving the optimization problem

$$\min_{\mathbf{s} \in \Re^N} \|\mathbf{s}\|_{l_1} \text{ subject to } \mathbf{y} = \mathbf{\Phi \Psi s} \tag{2}$$

$$\mathbf{r} = \mathbf{\Psi s} \tag{3}$$

where $\mathbf{\Psi}$ is a transform (reconstruction) basis in which the input $\mathbf{x}$ can be represented sparsely as $\mathbf{s}$. $\mathbf{\Psi}$ must also be incoherent (have a low correlation) with $\mathbf{\Phi}$. $\mathbf{r}$ is then the reconstructed estimate of the original input $\mathbf{x}$.

Depending on the choices for $\mathbf{\Phi}$, the minimisation algorithm, and $\mathbf{\Psi}$, many different compressive sensing implementations are possible, with differing performance levels. For $\mathbf{\Phi}$ we use a matrix with entries drawn from a 0 or 1 Bernoulli distribution, $p = 0.6$. Zero or one entries reduce the matrix multiplication required to an accumulation, eliminating the need for an explicit hardware multiplication stage and greatly reducing the processing load in the sensor node [7], [8]. We then use a Basis Pursuit optimization procedure [13] to solve the $l1$ problem of (2), as it is an iterative algorithm ensuring strongly polynomial running time. This is used with a cubic B-spline dictionary for $\mathbf{\Psi}$ [14]. The suitability of B-spline dictionaries for use with sparse problems has been established previously [15], and they have been found to be the most suitable basis for use with EEG signals [12].

Finally, all data are analysed in non-overlapping frames 750 samples long ($N = 750$). Results using $N = 375$ were generated but did not give any meaningful change in reconstruction performance and so are not reported here.

B. Analysis data

The four electro-physiological signals used in this work are described below, all of which have the d.c. offset attenuated using a 0.16 Hz first order filter before processing. Ten minute sections of single channel data have been analysed with three different examples of each signal used. For the EEG, ECG and EMG the three records come from different people. For the EOG, records 1 and 2 are from the same subject, but with the eyes open in record 1 and closed in record 2.

1) EEG: Channel C4 sampled at 208 Hz is used here, with these data being a sub-set of those reported in [16]. In addition, to demonstrate the impact of sampling frequency on the compressive sensing performance new awake EEG sampled at 2000 Hz has been recorded as part of this work and a further three records of this are analysed.

2) ECG: Records 107, 118, and 119 of ECG data from the MIT-BIH arrhythmia database [17], [18] are used here. These data are sampled at 360 Hz, and mirror the ECG data used in [7].

3) EOG: New EOG recordings of voluntary eye movements have been performed by the authors for analysis here. Left eye movements sampled at 1000 Hz are used.

4) EMG: Records slp32, slp37, and slp41 of EMG data from the MIT-BIH polysomnographic database [17], [19] are used here here. This data is sampled at 250 Hz and recorded from the chin as part of a sleep study.

C. Performance metrics

There are many different metrics that can be used for assessing the reconstruction error introduced by a lossy compression scheme and no consensus as to the most suitable [12]. Ideally the RMS (Root-Mean-Square) of the error $(\mathbf{x} - \mathbf{r})$ should be lower than the RMS noise intrinsically added by the recording electrodes and amplifiers. However the RMS is not suitable for comparing between signals as it is an absolute measure. Instead we quantify the reconstruction error with the commonly used Percent of Root-mean-square Difference (PRD):

$$\text{PRD} = \sqrt{\sum_i (x_i - r_i)^2 \Big/ \sum_i x_i^2} \times 100\% \tag{4}$$

where i is the sample number. Lower PRD numbers represent better reconstruction performance. It is calculated over a 10 s duration, giving 60 PRD values for each analysed record. The maximum, minimum and median values from these distributions are plotted.

III. RESULTS

Fig. 1 shows examples of reconstructed EEG, ECG and EMG signals after compressive sensing at a compression ratio of 0.19 (140/750). For EEG and ECG the original signal is successfully reconstructed from the under-sampled compressively sensed samples. The QRS macro-structure of the ECG signal is particularly well preserved, allowing heart rate determination. Introduced distortion is apparent however, and this is particularly so for the EMG signal.

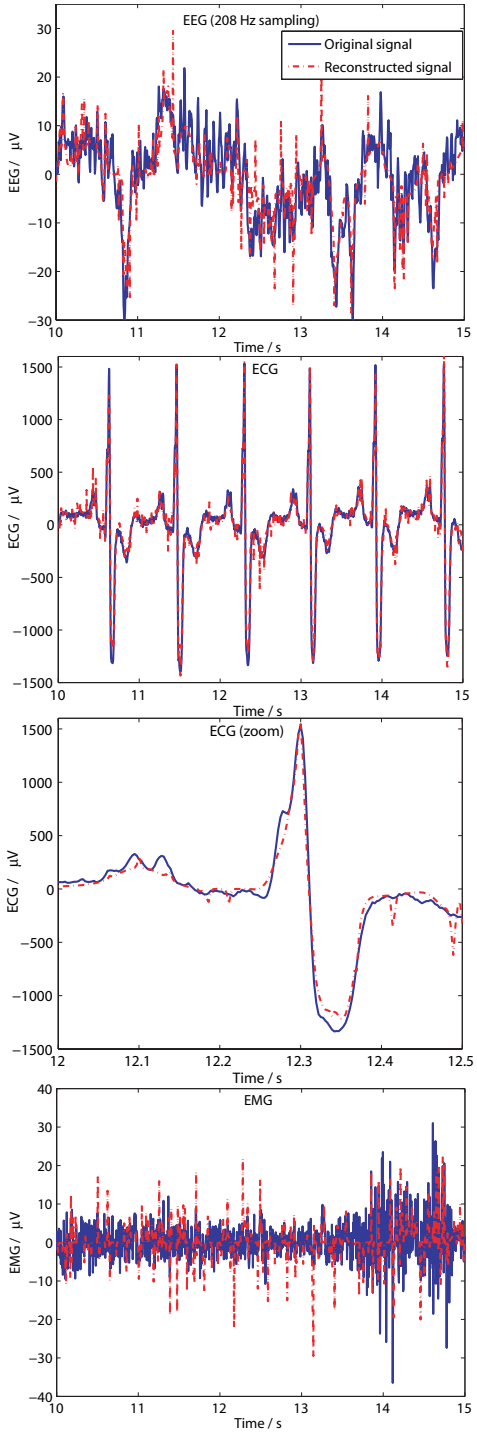

Fig. 1. Reconstructed EEG, ECG and EMG signals at a compression ratio of 140/750. A shorter time slice of the ECG signal is also illustrated.

This is quantified for the four electro-physiological signals in Fig. 2. Considering the median PRD values, at the lowest compression ratios the reconstruction performance is poor in all cases with approximately 100% PRD. As less compression is provided, in the EEG, ECG and EOG cases the error reduces substantially and successful reconstruction is achieved. The EOG and ECG signals are reconstructed particularly well. In contrast the EMG performance is poor in all cases and a satisfactory reconstruction is never achieved.

The maximum and minimum PRD values shown in Fig. 2 illustrate that large variances are present in the performance at each compression ratio. This variance occurs both within the same record and between the three example signals (intra- and inter- subject variation). As a result, although on average ECG records have better reconstructions than EEG records, in many cases the ECG performance would be substantially worse than the EEG. Similarly, although the higher sampling frequency EEG does get consistently better median performance than the lower sampling frequency EEG, it is within the inter- and intra- subject variation to be expected. It is likely that the acceptability of the approach is dominated by this variation in performance that can be tolerated, not by the average level of performance.

IV. DISCUSSION AND CONCLUSIONS

Our results demonstrate that signal agnostic compressive sensing is possible for EEG, ECG and EOG signals. At a compression ratio of 0.4 these are all reconstructed well and the median PRDs can be within previously established limits for successful use of the signals. For the ECG, the PRD of record 1 is 2.6%, in-line with the performance obtained in [7], and well below the 9% PRD previously determined as a *good* reconstruction [20]. For the EEG the absolute PRD is higher, although [21] suggested that up to 30% PRD could be tolerated without affecting the performance of an automated EEG processing algorithm. EOG signals obtained the best reconstruction performance, although these were also the most oversampled (natural bandwidth 30 Hz, 1000 Hz sampling) of the signals used.

The requirement to select $\mathbf{\Psi}$ on a signal-by-signal basis is therefore not mandatory for these signals. Indeed, in all of the cases considered the reconstruction performance is highly variable, and this variance in performance is much larger than the shift in median performance between the different electro-physiological signals. Therefore it is likely that performance variance dominates the overall usefulness of compressive sensing in Body Area Network applications. As opposed to considering $\mathbf{\Psi}$ on a signal-by-signal basis, the signal agnostic results here thus motivate the use of a time-varying approach for future compressive sensing. In this $\mathbf{\Psi}$ might change between frames of the same signal rather than only between signals.

The signal agnostic results have also allowed the comparison of performance across signals, and showed that the EMG signal was never satisfactorily reconstructed. The PRD is above 50% in all cases. Better performances may be achievable using different reconstruction bases ($\mathbf{\Psi}$), or by starting from higher base sampling frequencies—EMG signals may contain components up to 450 Hz, but the data used here were band limited and used a 250 Hz sampling rate. All of the other signals used were sampled much quicker than their *natural* bandwidths. However the current result is of note as EMG artefacts are a well known corrupting factor in EEG, ECG and EOG recordings. It suggests a potential new approach for motion artefact identification based upon compressive sensing, which should be explored further.

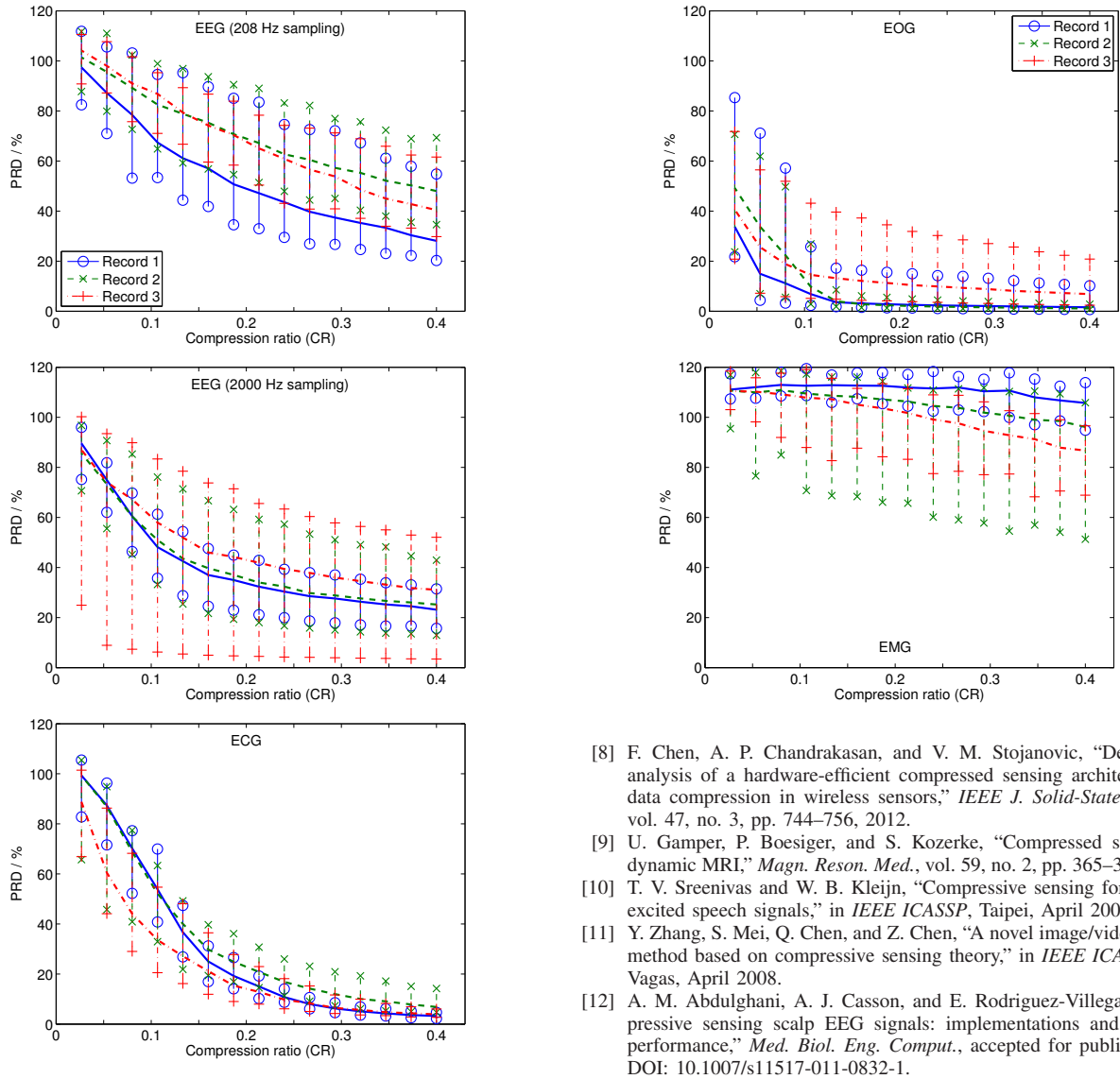

Fig. 2. PRD reconstruction performance of the compressive sensing scheme on EEG, ECG, EOG and EMG signals. Vertical lines show the maximum and minimum PRD values found during the reconstruction process. The median PRD value at each compression ratio is plotted from left to right.

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