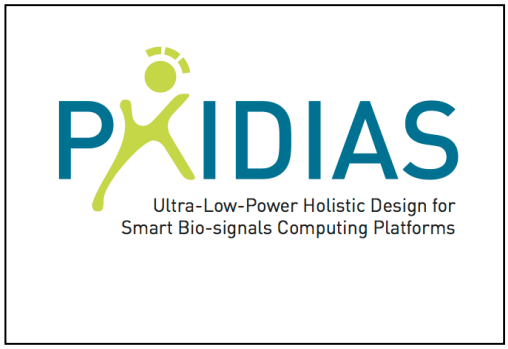
Deliverable report for



P H I D I A S

"Ultra-Low-Power Holistic Design for Smart Biosignals Computing Platforms"

Grant Agreement Number 318013

Deliverable D 1.1
Report on database of bio-signal features for consortium use

Due date of deliverable: 31/03/2013

Lead beneficiary for this deliverable: IMEC-NL
Contributors:
- **IMEC-NL:** collection of adaptively-sampled ECG bio-signals, document revision
- **EPFL:** collection of swallowing bio-signals, selection of publicly available bio-signal, initial sparsity analysis

Dissemination Level:		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

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Draft of the WP Leader	
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1. Description of task

This report describes the different features of bio-signals that compose the test set that will be used for the duration of the project. It also provides a validation of an unstructured sparsity analysis of the signals, which constitutes a baseline over which more advanced sparsity recovery methodologies will be evaluated.

2. Description of work & main achievements

2.1. Rationale and guidelines for constructing the bio-signal database

The Phidias project aims to investigate the opportunities offered by harnessing sparsity of bio-signals in order to efficiently acquire and compress them. A necessary step in this context is to identify proper bio-signals for investigation.

The chosen signals satisfy two important requirements. First, records should originate from a variety of bio-signal sources, offering the possibility to evaluate sparsity-based methodologies such as Compressed Sampling (CS) as a "universal" tool for low-power acquisitions. Second, the database should include a varying number of input channels and sampling rates, which will be instrumental in evaluating the efficiency of dedicated CS platform (either analogical or digital implementation) under different workloads.

To address variety, we included electrocardiogram (ECG), electroencephalography (EEG) and electromyography (EMG) records. ECG, EEG and EMG reflect the electrical activity of the heart, brain and skeletal muscles, respectively. They are commonly used in the clinical practice in many scenarios, such has diagnosing heart malfunctions or recovery from myocardial infarctions (ECG), investigating sleep and patterns and epilepsy seizures (EEG), monitor muscular activation (EMG).

All three classes of signals are acquired from electrodes, which capture the change in the electrical field around the area of interest. Other methods to capture bio-signals include readouts from (multi-axes) accelerometers and microphones. Both these sources are useful to detect abnormal conditions during swallowing, such has dysphagia.

Different bio-signal analyses generate a wide range of workloads. It is important to capture this aspect to design proper architectural solutions for the target CS platform. Records include in the DB range from ambulatory ECG signals sampled at a low resolution to more demanding EEG signals recordings presenting many signals acquired in parallel.

As far as possible, we relayed on standard databases, publicly accessible from the

widely-used Physionet website[1], to increase the reproducibility of results. We relayed on internal resources for swallowing signals, for which a standard database is not available at the moment. One research direction we are actively pursuing investigates the benefits of combining two sparsity-derived techniques: Adaptive Sampling (AS) and CS. To do so, the project partner IMEC-NL has made available an adaptively-sampled version of the popular MIT-Arrhythmia database (the original DB is distributed on Physionet).

2.2. Signal database content

Table 1 summarizes the records contained in the database. The records described in the rows 1, 3, 4, and 5 of the table are publicly available on the Physionet portal. Records described in row 2 derive from applying AS to the MIT-BIH Arrhythmia database. AS, which the Phidias partner IMEC-NL, is currently investigating, is a technique that dynamically adjusts the sampling rate according to the input dynamics. Records referred in line 6 being collected by the Phidias partner EPFL, using acquisition nodes developed internally.

	Name	Type	Number of records	Average Length	Sampling Frequency (Hz)
1	**MIT-BIH Arrhythmia (MIT-DB)**	2-channels ECG	48	30 mins	360
2	**Adaptive Sampled MIT-BIH Arrhythmia**	2-channels ECG	20	10 mins	360 / 90
3	**PTB Diagnostic ECG Database (PTB-DB)**	14-channels ECG	549	1-2 mins	1000
4	**CHB-MIT Scalp EEG (CHB-DB)**	23-channels EEG	664	1-4 hours	256
5	**CAP Sleep Database (CAPSLP-DB)**	EMG	108	1-4 hours	512
6	**Swallowing (Swall-DB)**	Accelerometer	30	5 min	10KhZ

Table 1: Bio-signal DB content and characteristics

The database includes different bio-signal modalities: ECG, EEG, EMG and swallowing. It also features records acquired using different devices physical devices: electrodes and accelerometers. Finally, it presents different requirements in terms of number of channels and sampling rate (from 90 Hz for the low-frequency setting in the AS MIT-BIH Arrhythmia, up to 1.25 KHz in the case of the swallowing database).

The various signal modalities will present different dynamics, allowing assessing the performance of CS as a "universal" encoding for bio-signals. The varying number of channels and sampling rates will determine the architectural choices for the CS solutions explored by the project partners, demanding different performance/energy consumption trade-offs.

1 http://www.physionet.org/

2.3. Initial investigation of the database bio-signals sparsity

Compressed Sensing (CS) exploits the sparse nature of biological signals for sampling at rates much lower than the traditional limits defined by the Nyquist - Shannon theory. In other words, CS assumes that bio-signals admit a very compact representation in a carefully designed base (or dictionary). In this Section, we provide an initial sparsity analysis of the database signals, to be considered as a baseline over which more advanced sparsity -aware techniques will be evaluated.

2.3.1. Mathematical background

Let the signal $x \in R^N$ be a real-valued N-dimensional vector. x can be represented in terms of N coefficients α_N in a basis $\Psi_{NxN} = [\psi_1 | \psi_2 | ... | \psi_N]$ via $x = \Psi\alpha$, where each column ψ_i is a vector, and α represents the coefficients vector. The signal x has a *sparse* representation if only $K << N$ entries of α are nonzero. In other words, a signal x is sparse if it can be represented by linear superposition of K elements of an orthonormal basis Ψ, i.e., $x = \sum_{i \in \Sigma_k} \alpha_i \psi_i$, where Σ_k is the support set of the coefficients vector α and K defines the sparsity level.

Few structured signals are truly sparse; most often, they are instead *compressible*. If a signal is compressible, the values of $\alpha = [\alpha_1, \alpha_2, ..., \alpha_N]$, when sorted in decreasing order of magnitude, obeys the power decay law:

$$\alpha_i \le R \cdot i^{-\frac{1}{p}}, \quad i = 1,2,..,N$$

The smaller p is, the faster the magnitudes decay, and the more compressible a signal is. Such a signal is well approximated using a K-term approximation (with K small), consisting of the K largest entries of α and setting all other terms to zero. In essence, compressible signals ($p < 1$) are well approximated by sparse signals.

2.3.2. Analysis method

As an index to show how the coefficients decay for each underlying signals, we employed power decay plots. These plots represent the absolute values of the coefficient of the input signals, represented in the sparsity basis, sorted in a decreasing order and in a logarithmic scale. For the initial investigation, we employed *DWT transform* as a sparsity-inducing transformation and *Daubechies filters* as sparsity bases Ψ.
The faster the coefficients decay, the more compressible the original signal is. For each signal classes, we have found the best K-term approximation and corresponding SNR and PRD values (described in the next Section). These plots

shows how much of the original signal information is retained when represented by the best K-term approximation.

2.3.3. Performance metrics

To quantify the compression performance while assessing the diagnostic quality of the compressed ECG records, we employ the two most widely used performance metrics: compression ratio (CR) and percentage root-mean-square difference (PRD). The compression ratio is defined as the percentage of reduction in number of bits required to represent the signal after compression relative to the original representation:

$$CR = \frac{b_{orig} - b_{comp}}{b_{orig}} \cdot 100$$

The percentage root-mean-square difference (PRD), and associated signal-to-noise ratio (SNR), quantifies the percentage of error between the original signal vector x and the reconstructed $\tilde{x}$:

$$PRD = \frac{\|x - \tilde{x}\|_2}{\|x\|_2} \cdot 100$$

$$SNR = -20\log_{10}(0.01 \cdot PRD)$$

The link between the measured PRD and the diagnostic distortion are illustrated in **Table 2**, which classifies the different values of PRD based on the signal quality perceived by a specialist. These threshold values were adopted from a state-of-the-art study, which performed a semi-blind test involving expert cardiologists[2].

PRD	Reconstructed Signal Quality
0 ~ 2%	"Very good" quality
2 ~ 9%	"Very good" or "good" quality
≥ 9%	Not possible to determine the quality group

Table 2: PRD and corresponding quality class

2.3.4. Experimental results

2.3.4.1. Electrocardiogram Signals (MIT-DB)

Figure 1 shows the averaged power decay plots for the ECG signals from all records of the database for different number of samples N = [64, 128, 256, 512, 1024] (the plots are in logarithmic scale). It can be seen that for N = 256 a large portion of the

[2] Y. Zigel, A. Cohen, and A. Katz, "The weighted diagnostic distortion (WDD) measure for ECG signal compression," IEEE Trans. on Biomed. Eng., vol. 47, pp. 1422–1430, 2000.

signal obeys the power decay laws, i.e, decay faster than i^{-1} curve, which is shown by the red line on the plots. Figure 2 similarly shows the power decay curves for different selection for the filter length, L = [6, 10, 14, 16, 20]. The results are shown for the best number of samples (N = 256). A filter length of L = 10 has the best results, as the largest portion of the signal samples are below the -1 slope.

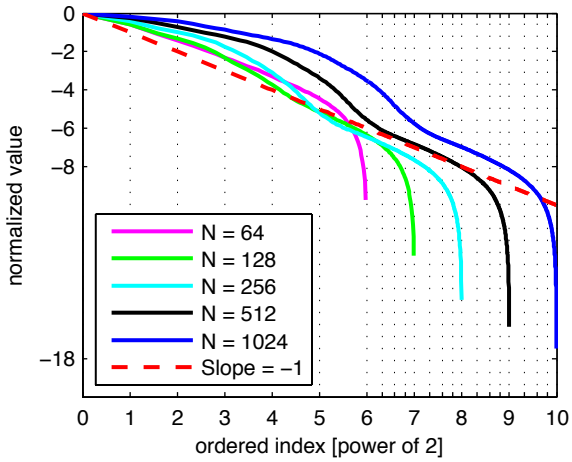

Figure 1: Power decay curves for different number of samples (MIT-DB)

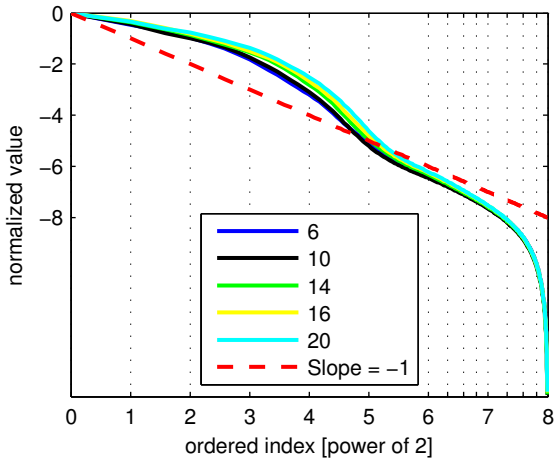

Figure 2: Power decay curves for different filter lenght and N= 256 (MIT-DB)

Other measures to quantify the sparsity level of the signal are the SNR and PRD for the best K-term approximation, which are illustrated in Figure 4 and Figure 3. In these figures, we have defined the compression ratio (CR) as the fraction of coefficients retained over the whole samples N, i.e, CR = K/N. In the plots values of the SNR corresponding to the "good" and "very good" signals quality are also indicated. For number of samples N = [256, 512, 1024] the performance are very similar and well above the other curves. Results show that only 30% and 10% of the coefficients are enough to reach "very good" and "good" signal quality, respectively, both for SNR and PRD metrics.

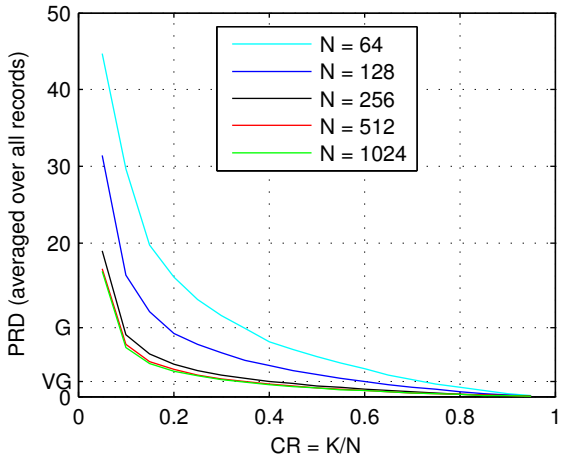

Figure 3: PRD vs. samples (N) for different compression ratios (MIT-DB)

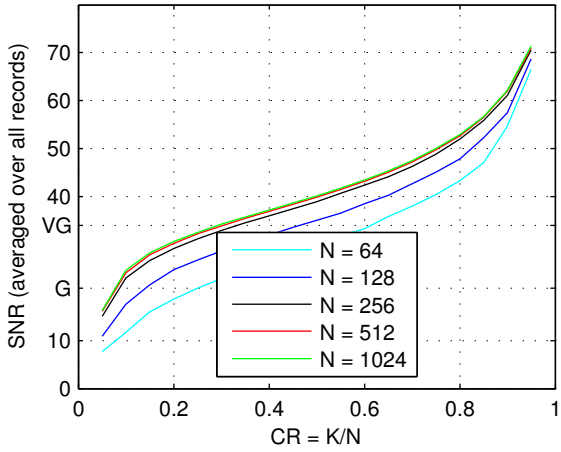

Figure 4: SNR vs. samples (N) for different compression ratios (MIT-DB)

2.3.4.2. Electrocardiogram Signals (PTB-DB)

The PTB database gives similar results with respect to the MIT-DB case, showing that compressed sensing is a valuable strategy for ECGs independently of the number of input signals (2-leads recordings for MIT-DB, 15-leads recordings in the case of PTB-DB).

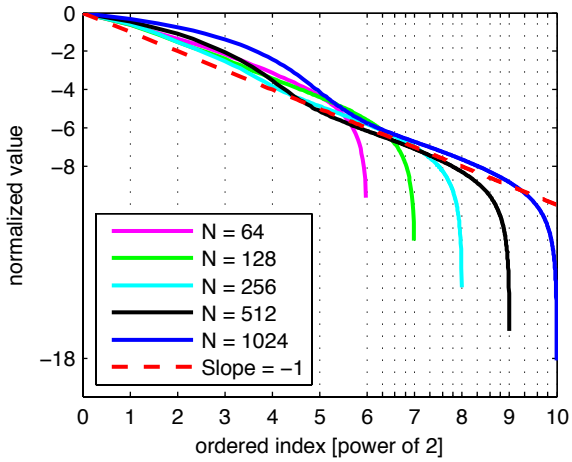

Figure 5: Power decay curves for different number of samples (PTB-DB)

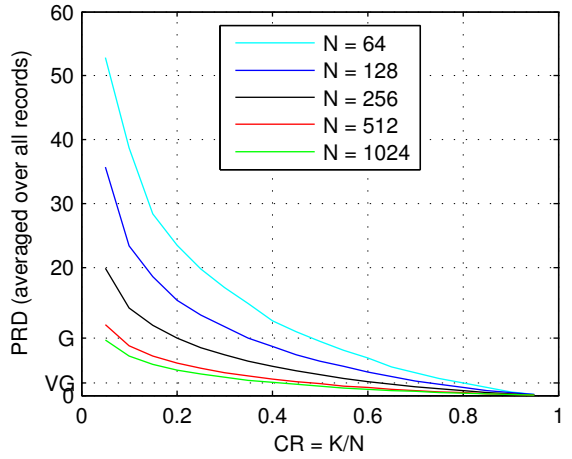

Figure 6: PRD vs. samples (N) for different compression ratios (PTB-DB)

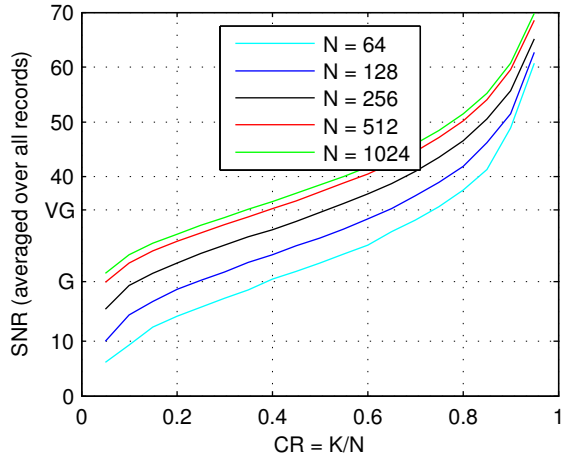

Figure 7: SNR vs. samples (N) for different compression ratios (PTB-DB)

2.3.4.3. Electroencephalogram Signals (CHB-DB)

To investigate the sparsity for the Electroencephalogram (EEG) signals, we have used the signals from (CHB-MIT) database. **Figure 8** shows the power decay curves averaged over all the records, which decade slower than in the case of ECG. Similarly **Figure 9** and **Figure 10** present the SNR and PRD curves for the EEG records averaged over all the records. As sparsity is not as prominent for EEG signals, the performance quality is lower than their ECG counterparts. SNR curves suggest that to reach the signal quality of 20 dB, 40 % of the coefficients should be preserved.

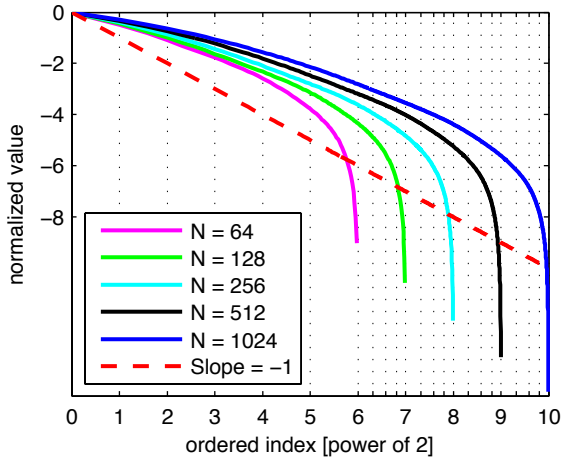

Figure 8: Power decay curves for different number of samples (CHB-DB)

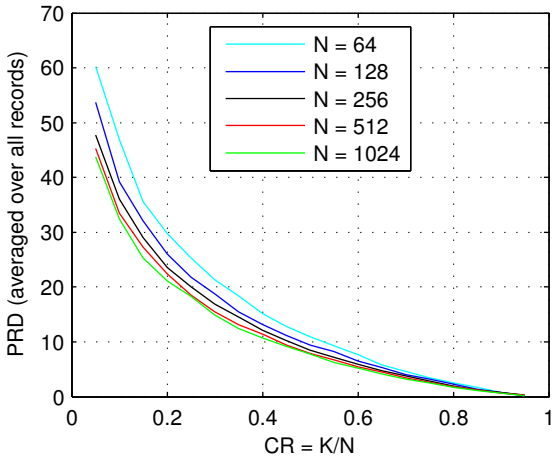

Figure 9: PRD vs. samples (N) for different compression ratios (PTB-DB)

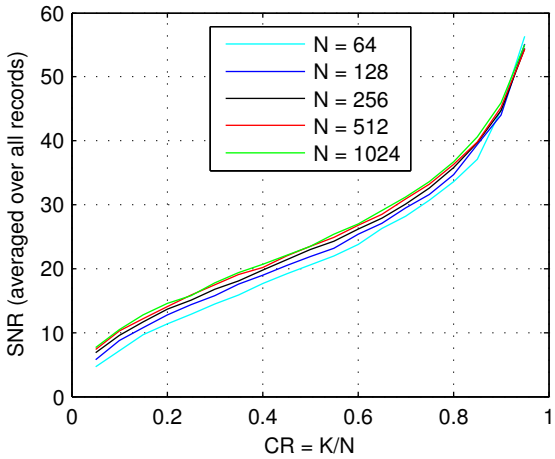

Figure 10: SNR vs. samples (N) for different compression ratios (PTB-DB)

2.3.4.4. Electromyogram Signals (SHHPSG-DB)

To investigate the sparsity for the Electromyogram signals, we have used EMG channels form the CAPSLP-DB. The EMG channels are from the submentalis muscle and bilateral anterior tibial EMG. The EMG channels with sampling frequency of 512 Hz are selected for analysis and the silent parts of the signal are removed. Figure 11 shows that power decay plots for the EMG recordings averaged over all the record, showing that a small number of coefficients obey the power decay law. These signals are therefore not well approximated by a sparse representation using Daubechies filters as a sparsity dictionary, hinting that more complex techniques must be used to achieve good results.

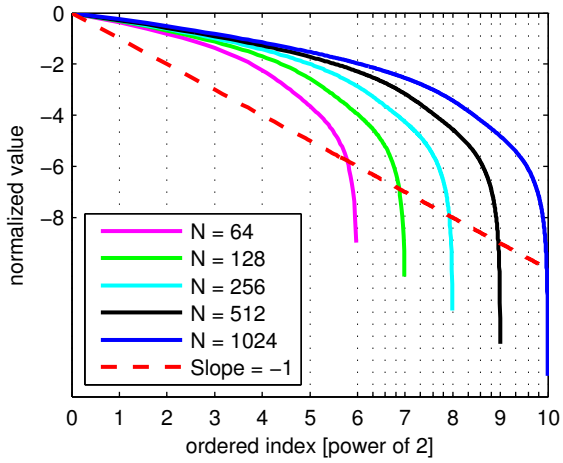

Figure 11: Power decay curves for different number of samples (SHHPSG -DB)

2.3.4.5. Accelerometry swallowing (Swall-DB)

Figure 12 shows the power decay plots for the swallowing records, averaged over all records of the database. As shown below, discrete wavelet coefficients of swallowing signals also are not well satisfying the power decay law, leading to poor compression

performance if high fidelity has to be retained.

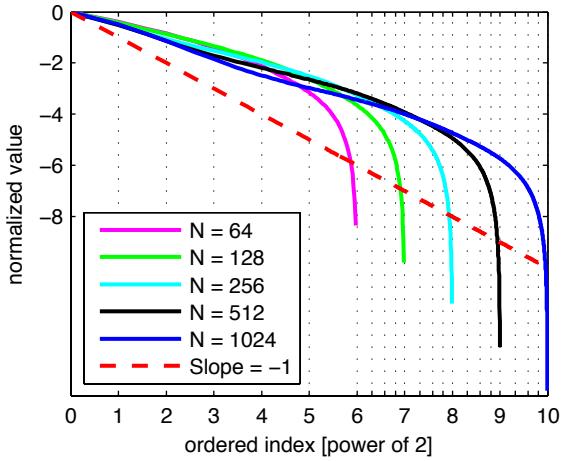

Figure 12: Power decay curves for different number of samples (SHHPSG -DB)

3. Performance of the partners

All partners fulfilled their tasks in satisfactory time and quality.

IMEC-NL performed an adaptive sampling of the MIT-Arrhythmia database, disseminating the resulting records to the consortium.

EPFL identified and collected the bio-signals data and performed the initial assessment of their sparsity level.

4. Conclusions

The Deliverable presents a database of bio-signals encompassing different modalities: ECG, EEG, EMG and swallowing data (acquired with an accelerometer). The considered records present a varying number of simultaneously acquired channels (from 1 to 23) and are acquired with diverse sampling frequencies (from 125 Hz to 10 KHz), thus requiring different workloads for the CS implementations that will be studied during the course of the project.

Furthermore, the deliverable presents an initial assessment of the sparsity of the different bio-signal modalities, investigating the power-decay curves of the signals and the SNR induced by compressed sensing for different compression ratios. We employed the digital wavelet transform as a sparsity-inducing transformation and Daubechies filters as sparsity bases. Experiments show that ECG is highly sparse under the considered settings; results from the EEG and swallowing databases are also encouraging, while EMG presents less sparsity and is therefore more challenging in the context of Compressed Sensing.

The Full Assembly deems this deliverable to be fulfilled satisfactory.