HIGH DIAGNOSTIC QUALITY ECG COMPRESSION AND CS SIGNAL RECONSTRUCTION IN BODY SENSOR NETWORKS

Mihaela I. Chidean[⋆], *Óscar Barquero-Pérez*[⋆], *Qi Zhang*[†], *Rune Hylsberg Jacobsen*[†], *Antonio J. Caamaño*[⋆]

[⋆]Dept. of Signal Theory and Communications, Rey Juan Carlos University, Spain
[†]Dept. of Engineering, Aarhus University, Denmark

ABSTRACT

Compression of electrocardiograms (ECG) in wireless environments, with diagnostic quality, has shown limited potential. This lack of quality preservation, using Wavelet Transform (WT), is due to the fact that the multiple levels of detail that can be achieved in the time domain are not exploited. In the present work, we propose to fully exploit the wavelet capability to operate at different levels of signal detail at different time scales. WT with an appropriate Compressed Sensing (CS) matrix is used in the electrode nodes of body sensor networks to encode and compress the ECG. Then, the signal is reconstructed using a basis pursuit denoise algorithm. Preservation of the diagnostic quality by means of standardized metrics is then tested for multiple wavelet bases and levels. High quality ECGs from 50 healthy patients are used to statistically show that diagnostic quality preservation is possible even at high compression rates. In these cases suitable ECG wavelets are required.

Index Terms— Body Sensor Networks, ECG, Compressed Sensing, Wavelet Transform.

1. INTRODUCTION

The development of small and portable ECG systems with low energy consumption has been a topic of interest for the last years [1–3]. Several achievements have been obtained, including a wireless Body Sensor Network (BSN) capable of sampling and transmitting a one-lead ECG [1]. The interest on such systems lies in the need for ambulatory patient monitoring or providing medical support in remote areas [4].

The sensing nodes have to provide support for a high computational load in typical BSN scenarios, since it is in charge of the ECG measurement and transmission to a central node. Thus, in order to preserve battery and to simplify the sensing node, compression techniques are mandatory.

Several approaches have been proposed and Compressed Sensing (CS) [5] is one of the techniques mostly used in related works. CS assumes that the ECG signal has a sparse projection in a given domain and that it is possible to recover the signal from a small set of coefficients by using optimization techniques. One of the most frequently used domains for ECG signals are the different wavelet transform (WT) bases functions [1, 3, 6]. Some authors assume also a time-domain sparsity for the ECG signal [2]. The CS technique lowers the computational demand on the sensing node in portable scenarios. Therefore, the combination of CS and WT for a portable ECG system is appropriate as it takes advantage of both the sparsity of the ECG signal in the wavelet domain and the usage of a compression technique with low computational cost.

Previous works that use CS and WT for ECG signals reported good results, in terms of the signal quality of the recovered ECG, after a coding/decoding process. However, these studies compared the quality results using central tendency statistics (mean, median). This approach omits information from signals recovered with poor quality as the patterns in these situations are not normal (tachycardia, flutter, ectopic), which are otherwise crucial from a clinical point of view.

The goal of the present work is to greatly improve the quality of the reconstructed ECG by means of the WT, with different bases and levels, at high Compression Ratios (CR). We will validate the proposed method with a statistical analysis of the results of compressing and recovering high-quality ECG segments from 50 healthy patients. This analysis will also allow us to answer the question of which is the best combination of wavelet bases and levels to achieve high CR preserving the diagnostic capabilities of the ECG.

In the following, we present the system setting and provide definitions for the different mathematical tools that we use in Section 2. Next, we describe the methodology used to validate our hypothesis through computer experiments in Section 3 and explain the results obtained in Section 4. Finally in Section 5, we present the conclusions of the present work.

2. SYSTEM SETTING

In this section, a brief introduction to CS and WT is first provided. Next, the hypotheses proposed in this work are detailed.

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2.1. Compressed sensing

CS is a sampling technique that exploits the compressibility of the signal of interest $\mathbf{x} \in R^N$, resulting in the measurement $\mathbf{y} \in R^M$ [5]. The main idea behind CS is that the signal $\mathbf{x}$ is sparse in some basis, meaning that only K out of N coefficients of $\mathbf{x}$ have significant information ($K << N$). In this situation, the signal $\mathbf{x}$ is known as K-sparse. Formally,

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

where $\mathbf{\Phi} \in R^{M \times N}$ is the sensing matrix and $\mathbf{\Psi} \in R^{N \times N}$ is the transformation basis where the signal $\mathbf{x}$ is $K-$sparse (also known as sparsity basis). The recovery of the signal sampled with CS is usually based on L1 optimization.

The key fact in CS is the relation between the two involved matrices. Specifically, the random sensing matrix has to fulfill the *Restricted Isometry Property* (RIP) [7]. The verification of this property is complicated and multiple metrics were proposed in the literature to replace the RIP, e.g. the mutual coherence [8]. However, one of the most common choices for the sensing matrix $\mathbf{\Phi}$ are random matrices with independent identically distributed entries formed by sampling Gaussian or Bernoulli distributions. In practice, these type of matrices perform fairly good and even can be efficiently constructed in resource-limited devices as the one used in BSNs [1].

The relation between the size of the original signal N and the size of the compressed signal M is known as CR, and is usually defined as

$$CR = \frac{N - M}{N} \times 100 \tag{2}$$

With this formulation, lower values of CR lead to low data compression. In other words, $CR = 5$ means that the system transmits 5% less data compared with the no compression.

2.2. Wavelet transform

WT is an orthogonal expansion technique that uses *wavelets* as basis functions, which are oscillating functions whose energy is concentrated in time [9]. Wavelets are organized on different families, e.g. Haar, Daubechies (*db*), Reverse Biorthogonal (*rbio*), etc. Each family has its own special properties and benefits to sparsely represent different signals.

WT allows to express the ECG signal as a linear combination (series expansion) of the basis function (wavelets), $\mathbf{\Psi}$. Specifically, if $\mathbf{x}$ is the signal of interest, the wavelet coefficients α can be computed as

$$\alpha = \mathbf{\Psi}\mathbf{x} \tag{3}$$

On the other hand, the signal of interest can be reconstructed from the wavelet coefficients with

$$\mathbf{x} = \mathbf{\Psi}^\top \alpha \tag{4}$$

since WT is an orthogonal transform. The $(\cdot)^\top$ notation indicates the transpose operation.

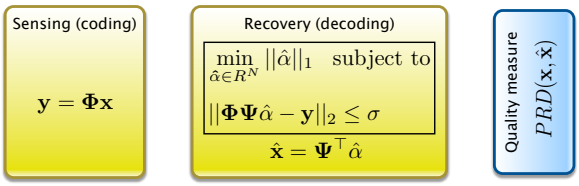

Fig. 1. Problem statement and experimental scenario. The sensing procedure is performed in a resource-limited ECG sensing node. The data is then sent to a high-capability node that performs the reconstruction of the ECG record.

2.3. Problem statement

Within the framework of mHealth systems based on a BSN for ECG measurement and monitoring, the variability of the results of compression throughout many patients is not usually examined. Quality analysis that omits this aspect would lead to compression schemes useless from a diagnostic point of view, as even in healthy ECG signals there are events that alter the WT coefficients. Thus, the evaluation of a BSN in terms of a given metric averaged over multiple ECG signals measured from independent human subjects is insufficient to ensure proper operation for broad compression ranges.

In this work we analyse a BSN system outlined in Figure 1, where the CS coding is performed directly over the original ECG $\mathbf{x}$. The ECG sensor node only requires computational capabilities to perform the linear operations involved in the CS sampling and to transmit the sampled signal $\mathbf{y}$. In this figure, the notation $||\cdot||_l$ and $\hat{\cdot}$ indicate respectively, the l-norm and a recovered signal.

The decoder receives $\mathbf{y}$ and, as $\mathbf{x}$ is sparse in the wavelet domain spanned by the basis $\mathbf{\Psi}$, it recovers the wavelet coefficients $\hat{\alpha}$ solving a L1 optimization problem, i.e. the basis pursuit denoising problem. The σ parameter models the noise level. Finally, the ECG signal is reconstructed using the coefficients $\hat{\alpha}$ and the inverse wavelet transform.

The quality metric used is the *Percentage Root-mean square Difference* (PRD) [10]. This scenario is frequently used in related works [1], as the computational burden and the memory requirements for the ECG sensor node are low.

3. EXPERIMENTS

This section describes the experiments performed in order to assess the variability of the quality results throughout multiple patients. First, we describe the ECG database and the experimental setting with all the cases considered in our analysis. Next, the quality metric, used to compare the original ECG with our experimental results, is explained. And finally, we describe the expected output, that will be discussed in Section 4.

3.1. Database

We use the PTB Diagnostic ECG Database [11] in our computer experiments. This database contains records of 15-lead

Table 1. PRD vs. reconstructed ECG quality [17]

PRD	Quality group
0–2	"Very good" quality.
2–9	"Very good" or "good" quality.
≥ 9	Not possible to determine the quality group.

ECG sampled at 1 KHz with 16-bit resolution. From all the records available in this database, we use $P = 50$ signals with a duration of approximately 12 seconds, all from healthy ECGs. The analysis of each signal is performed by frames, each frame of $N = 2^{12}$ samples; the frame length is selected to have similar time extent as similar works, such as [12].

3.2. Experimental setting

We simulate the scenario plotted in Figure 1 for a given ECG record. The sampling is performed by applying CS directly to the ECG signal and the recovery of the signal is based on solving a L1-minimisation problem where the objective is to derive the wavelet coefficients of the ECG. In this work, we use the basis pursuit denoising algorithm provided by the SPGL1 solver [13].

Regarding the sensing matrix, we follow a previous method where $\mathbf{\Phi}$ has exactly d non-zero elements per column equal to $1/\sqrt{d}$ [1]. This method has a low computational cost thus facilitating its implementation in an actual BSN device. In this work, we simulate four levels of CR, namely $CR \in \{20, 40, 60, 80\}$ and for each level, we consider two different cases, i.e. $d = 6$ and $d = 12$. For statistical significance, we use 10 different random sensing matrices for each combination of parameters.

For the sparsity basis, we use several wavelet functions, namely: 1) *db4*, often used [12, 14]; 2) *db10*, stated in [1] as the most popular wavelet basis for analysis; 3) *rbio1.5*, regarded as a baseline; 4) *rbio 3.7*, stated as the best wavelet basis for ECG in [15]; 5) *rbio4.4*, commonly used for ECG compression [16]. To analyse the behaviour and the quality at multiple resolutions, for each combination of CR-d-wavelet we recover the ECG using up to 7 wavelet levels, independently.

3.3. Quality metric

PRD quantifies the error in percentage among the original ECG $\mathbf{x}$ and the reconstructed one $\hat{\mathbf{x}}$ and is defined as [10]:

$$PRD(\mathbf{x}, \hat{\mathbf{x}}) = \frac{||\mathbf{x} - \hat{\mathbf{x}}||_2}{||\mathbf{x}||_2} \times 100 \qquad (5)$$

PRD and the quality of the reconstructed ECG are related as summarized in Table 1. This link has been established by Zigel *et al.* [17], where multiple specialists quantified the similarity between original and reconstructed ECG with different values of PRD. This metric is used very often as a performance metric in ECG studies and low values of PRD amount for low distortion among the original and the reconstructed data.

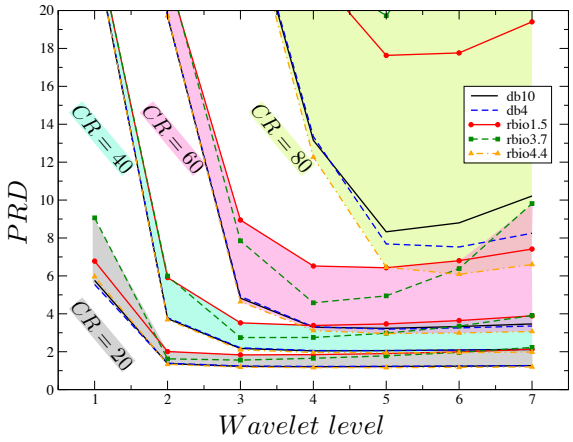

Fig. 2. PRD averaged over the entire database for each combination of the $CR \in \{20, 40, 60, 80\}$, wavelet basis $\in \{$*db4*, *db10*, *rbio4.4*, *rbio1.5*, *rbio3.7*$\}$ and level $\in \{1, 2, \ldots, 7\}$ used in the experiments. Results for $d = 12$ are shown.

3.4. Experimental outcomes

The main outcome of our computer experiments that will be analysed in the following section is the PRD. And in our analysis we will use two degrees of data aggregation for each combination of parameters:

- Average PRD over all the records in the database.
- Boxplot of the PRD obtained for all the records in the database. Each boxplot is built with $P = 50$ values.

4. RESULTS

In this section the results obtained from our computer experiments are analysed. First, we analyse the average PRD results, to determine the best wavelet basis in this scenario. Finally, we detail our analysis considering the distribution of the PRD and the differences between all the ECG records.

4.1. Average PRD – the "best" wavelet basis

Following the methodology used in similar works, in Figure 2 we plot the PRD averaged over all the records in the database, for the $d = 12$ case. The y-axis has been limited to $PRD = 20$, as higher values do not provide relevant information and also hinder the interesting part. In this figure, we observe the expected difference in quality between the different CR considered, i.e. the higher the CR, the lower the quality for the recovered signal. Within each CR level, there are two different quality groups that correspond to the wavelets $\{$*db4*, *db10*, *rbio4.4*$\}$ and $\{$*rbio1.5*, *rbio3.7*$\}$, respectively.

The wavelet basis with the worst performance is clearly the *rbio1.5* one, but the wavelet basis with the best performance is less conspicuous. In all cases, the *rbio4.4* basis functions always have the lowest PRD compared with the others, but with such small difference between these three cases (less than 10^{-2} for $CR = 20$) other criteria have to be considered to determine which to use in an actual system, such as the

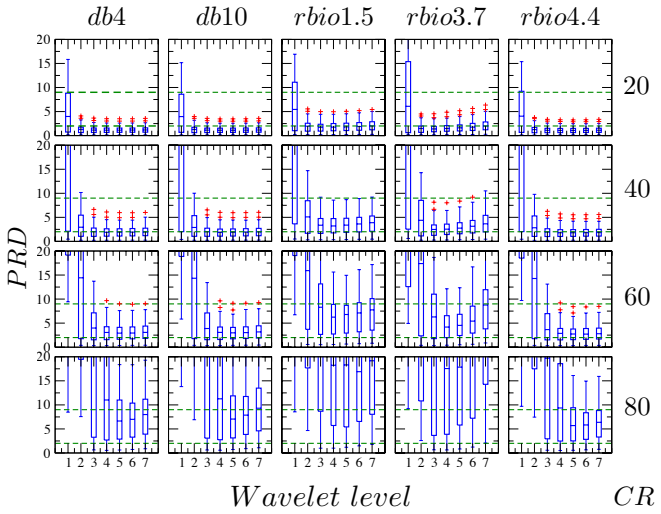

Fig. 3. Distribution of the PRD seen as boxplot for multiple combinations of CR, wavelet basis and level and for $d = 6$.

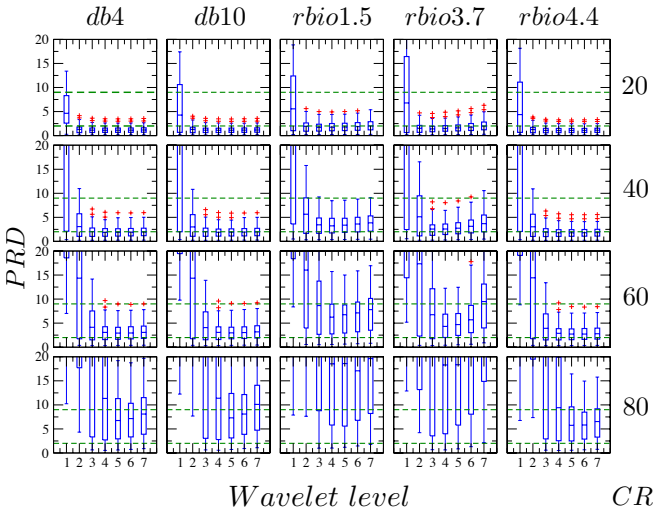

Fig. 4. Distribution of the PRD seen as boxplot for multiple combinations of CR, wavelet basis and level and for $d = 12$.

computational burden, the used memory or the symmetry of the basis functions.

The analysis for $d = 6$ is similar and leads to almost identical conclusions.

4.2. PRD boxplot

In contrast to the previous section, now we analyse the distribution of the PRD obtained, using the boxplot procedure. In Figures 3 and 4 can be found for $d = 6$ and $d = 12$, respectively, and for the different CR, wavelet basis and wavelet levels simulated. In these figures, the dashed green lines represent the $PRD = 2$ and $PRD = 9$ thresholds, the blue symbols are for the boxplot representation, the red symbols are for the outliers, i.e. the PRD value located at a distance higher than 1.5 the inter-quartile range. Minor differences are observed among the two figures, but a significant benefit enhances the $d = 6$ case, i.e. in an actual ECG sensor node half the memory is needed to store the sensing matrix $\mathbf{\Phi}$.

Again, the higher the CR the lower the quality obtained, but interestingly, the higher the inter-quartile range (the dispersion). With this representation it is clear that the average of each boxplot is not the most representative statistic.

Regarding the exact values, as a general rule, the first wavelet level performs worse than higher levels, especially at lower values of CR. The interesting fact is that for $CR <= 40$ all the wavelet bases result in PRD values that are ranged in the "very good" and "good" quality groups for ECG (i.e. $PRD < 9$). In general, to determine the "best" wavelet basis is not as straightforward and the dependence on the application requirements is more apparent. For BSN with less compression requirements the baseline *rbio1.5* is still useful and is a symmetric wavelet with a simple implementation. The *db4*, *db10* and *rbio4.4* are clearly preferable in the case of high compression requirements (up to $CR = 60$). In this cases the wavelet level is also a relevant parameter, and its choice determines a system that performs properly or not in terms of PRD. Finally, for $CR = 80$ and wavelet level higher than 5, the same wavelets provide low values of PRD for more than 50% of the records.

These results clearly show that the performance of an actual BSN depends on several factors such as the CR and the wavelet basis and level used. But the most important factor is the person who uses the system and any validation method that includes any kind of average over ECG signals is not as adequate as possible.

In all cases there are ECG records that lead to fairly good quality ($PRD < 2$), even at high level of data compression such as $CR = 80$. This fact highlights the large differences between the records, all of them classified as "healthy". These findings encourage us to further analyse the dependence between the PRD and the ECG record within the framework of wide dispersion between similar patients.

5. CONCLUSIONS

In this work we have found that averaging the PRD is not an appropriate method to evaluate the performance of an ECG mHealth solution, as the quality results of similar ECG records show high variance. For this purpose, we have performed experiments with actual ECG records, all classified as coming from healthy patients and we have observed that even healthy subjects lead to quality results with high dispersions.

From our experiments, we can also state that the selection of the wavelet basis used in the ECG system depends on the final application. If no high compression rate is needed bases with lower computational burden are still useful, such as *rbio1.5*. On the other hand, at higher compression rates, the wavelet basis and the level selections are more critical. For example, at $CR = 80$, *rbio4.4* can achieve the $PRD < 9$ at any level above 5 for 75% of the ECG records. Other considered wavelet bases achieve lower performance than *rbio4.4*.

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