BULETINUL INSTITUTULUI POLITEHNIC DIN IAŞI
Publicat de
Universitatea Tehnică „Gheorghe Asachi” din Iaşi
Tomul LX (LXIV), Fasc. 2, 2014
Secţia
ELECTROTEHNICĂ. ENERGETICĂ. ELECTRONICĂ

COMPRESSED SENSED ECG SIGNALS USING PATIENT SPECIFIC DICTIONARIES

BY

MONICA FIRA[1,*] and LIVIU GORAŞ[1,2]

[1]Institute of Computer Science, Romanian Academy, Iaşi, Romania
[2]“Gheorghe Asachi” Technical University of Iaşi
Faculty of Electronics, Telecommunications and Information Technology

Received: April 10, 2014
Accepted for publication: June 16, 2014

Abstract. In this paper we investigate the reconstruction of compressed sensed ECG signals using patient specific dictionaries and several types of projection matrices (matrices with random i.i.d. elements sampled from the Gaussian or Bernoulli distributions, and matrices optimized for the particular dictionary used in reconstruction by means of appropriate algorithms). We analysed two ways of building dictionaries used in the reconstruction phase, *i.e.*, with and without centered *R*-wave. The best results were obtained with optimized projection matrix with respect to the dictionary and patient specific dictionary with centered *R*-wave.

Key words: compression; ECG; signal processing; compressed sensing.

1. Introduction

Shannon’s sampling theory represents, in the case of many signal classes, a too severe limitation. It can be overcome by using the *Compressed Sensing Theory* (compressive sensing, compressive sampling and sparse sampling) thoroughly investigated in the last several years by prestigious researchers such as D. Donoho, (2006, 2004), E. Candès *et al*., (2008), M. Elad, (2007), etc. Compressed sensing (CS) is a rather new method which draws the

[*]Corresponding author : *e-mail*: mfira@etti.tuiasi.ro

attention of many researchers and is considered to have an enormous potential, with multiple implications and applications, in all fields of exact sciences. Specifically, CS is a compressing technique, essentially based on finding sparse solutions to underdetermined linear systems. In the signal processing domain, CS is the process of acquiring and reconstructing a signal that is supposed to be sparse or compressible from a reduced set of projection on a set of random signals.

In this paper we present a new ECG compression method based on the CS concept that requires an ECG signal preprocessing to delimitate the ECG signal in cardiac cycles (heart beat or cardiac patterns) to be compressed. The proposed method speculates the ECG signal specific features of each patient. Moreover three projection matrices needed for compression are analysed: a projection matrix built taking into account the dictionary that will be used in the reconstruction phase (decompression), a Bernoulli matrix type, and a Gaussian random matrix.

The paper begins with a section in which a brief review of CS is made, then the method is discussed and finally experimental data and conclusions are presented.

2. Background on Compressed Sensing (CS)

CS studies the possibility of reconstructing a signal, x, from a few linear projections, also called *measurements*, given the *a priori* information that the signal, x, is sparse or compressible in some known basis, Ψ. The vectors on which x is projected onto are arranged as the rows of an $n \times N$ projection matrix Φ, $n < N$, where N is the size of x and n – the number of measurements. Denoting the measurement vector as y, the acquisition process can be described as

$$y = \Phi x = \Phi \Psi \gamma, \tag{1}$$

$$\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}} \|\gamma\|_{l_0} \quad \text{subject to} \quad y = \Phi \Psi \gamma, \tag{2}$$

$$\hat{x} = \Psi \hat{\gamma}. \tag{3}$$

The system of eqs. (1) is obviously undetermined. Under certain assumptions on Φ and Ψ, however, the original expansion vector, γ, can be reconstructed as the unique solution to the optimization problem (2); the signal is then reconstructed with (3). Note that (2) amounts to finding the sparsest decomposition of the measurement vector, y, in the dictionary $\Phi\Psi$. Unfortunately, (2) is combinatorial and unstable when considering noise or approximately sparse signals. Two directions have emerged to circumvent these problems: (i) pursuit and thresholding algorithms seek a sub-optimal solution of

(2) and (ii) the Basis Pursuit algorithm (Chen, 1998) relaxes the l_0 minimization to l_1, solving the convex optimization problem

$$\hat{\gamma} = \underset{\gamma}{\arg\min} \|\gamma\|_{l_1} \quad \text{subject to} \quad y = \Phi\Psi\gamma, \tag{4}$$

instead of the original one.

In the past few years, the mathematic fundamentals of CS can also be found in application in the field of biomedical signals, both at the level of processing method (for ECG and EEG type signals), as well as at the level of implementation in practical applications, such as compression, transmission and reconstruction of the ECG signal using, for instance, a smart-phone (Mamaghanian *et al*., 2011; Polania *et al*., 2011; Zhang *et al*., 2013).

3. Method

Starting from the observations underlined by Fira *et al.*, (2010), that using a standard wavelet dictionary leads to worse results compared to using specific ECG signal dictionaries, we made a further step toward improving the compression rate and the reconstruction error by using a specific dictionary for each patient.

In a previous work (Fira *et al.* 2013) a compression method based on patient specific dictionaries and a dictionary made of segments of the first part of the patient's ECG signal was presented. Note that in that paper, the dictionary atoms are ECG random segments for which the *R*-wave can occur anywhere within the 256 samples or can even be absent. In this way, we speculated the ECG signal specific features of each patient without taking into account the cyclical pattern of the heart beats.

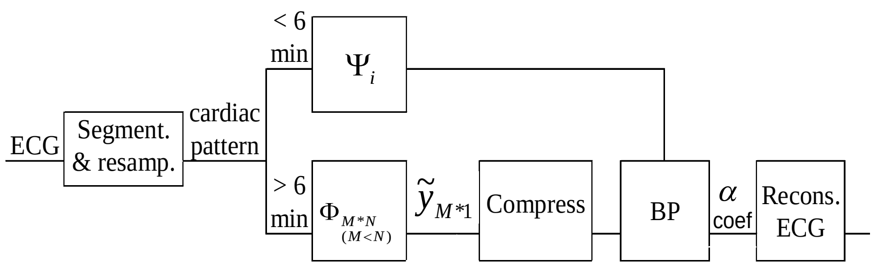

Fig. 1 – Principle of the method.

Indeed, the ECG signal is typically quasi-periodic, being composed of cardiac cycles repeating with rather low variability. Based on this observation, in some of our previous works (Fira *et al*., 2010; Fira *et al*., 2011; Fira *et al*., 2012) have proposed compression methods that employ pre-processed ECG signals, *i.e*. segmented in cardiac cycles, rather than directly with the ECG recording.

In this paper we propose a compression method, shown in Fig. 1, that exploits both cyclical heartbeat and patient specific characteristics. The ECG signal is pre-processed and converted into cardiac cycles; the first 6 min. from the ECG signal is used to build the patient specific dictionary. After these 6 min. the dictionary is built and one can pass to the effective ECG compressed sensing.

From the ECG recorded samples that are stored in the processing buffer, full cardiac beat cycles are extracted by detecting the maxima of the *R*-waves, followed by segmenting between the midpoints of consecutive *RR*-intervals.

3.1. Preprocessing Stage – Segmentation and Resampling

For using segments with no *R*-wave alignment, the extracted segments are subsequently resampled to 301 samples.

When *R*-wave alignment is desired, each ECG segment is split in two parts, one from the beginning of the segment to the location of the *R*-wave and the other one from there to the end, and each part are independently resampled to a length of 150 samples.

In this way, the cardiac beats are resampled to a fixed dimension of 301 samples, with the *R*-wave optionally aligned in the center of the segment.

3.2. Projection Matrices

It is known from the literature (Duarte *et al.*, 2005; Baraniuk *et al.*, 2005) and our previous works (Cleju *et al.*, 2011; Fira *et al.*, 2010) that the reconstruction quality of the compressively-sensed signal is influenced by the type of matrix used in the compression stage.

While most CS theory deals with signals which are sparse in orthonormal bases, the signals we deal with are sparse in a nonorthogonal basis, Ψ, of an overcomplete dictionary. Projecting on a matrix, Φ, with i.i.d. normal elements results in a system $y = \Phi\Psi\gamma = A_1\gamma$. However, if Φ is a random matrix, $A_1 = \Phi\Psi$, will have a higher RIP constant and, therefore, is likely not appropriate for reconstruction (Cleju *et al.*, 2011).

A better alternative is to use a projection matrix defined as $A_2 = \Phi\Psi^T$ (product of random matrices and the dictionary transposed), resulting in an acquisition eq. system $y = \Phi\Psi^T\Psi\gamma$. In our previous experiments (Cleju *et al.*, 2011), this results in the best reconstruction errors among the two alternatives. The reason is that the coefficients error vectors, $\gamma - \hat{\gamma}$, are, in this case, smaller along the directions of the significant singular vectors of Ψ.

A third possibility is to use a projection matrix composed only of 0 and 1 elements that are equally probable, *i.e.* a symmetrically distributed Bernoulli type matrix ($P(\Phi_{i,j} = 1/2)$), with a controlled way of generating the entries to ensure symmetry (half of the entries of a row are generated with the Bernoulli distribution and the other half by inverting the first half) (Fira *et al.*, 2013).

3.3. Dictionary Design Stage

This stage consists first of a standard recording of a 6 min. long ECG signal with no compression involved. This segment is then segmented into cardiac beats, with optional *R*-wave alignment, and the segments form the patient's dictionary. Thus, the dictionary is a matrix of size 301 × 700. This method speculates the quasi-periodicity and the particular features of the ECG signal of a certain patient.

After these 6 min. required for constructing the dictionary, one can start the procedure of compressively acquiring the ECG signal for the patient.

3.4. The Stage of Reconstruction of the Compressed Cardiac Patterns

The reconstruction of the compressed cardiac patterns is based on using the above discussed patient specific dictionary consisting of 700 cardiac patterns with or without centered *R*-wave of the specified class stored as 301 × 700 matrices. For reconstructing the patterns we use the Basis Pursuit algorithm to determine the coefficients.

3.5. Validation of the Compression Method

To validate the compression we evaluated the distortion between the original and the reconstructed signals by means of the percentage root-mean-square difference (PRD) and its normalized version, PRDN:

$$\text{PRD, [\%]} = 100\sqrt{\frac{\sum_{n=1}^{N}\left[x(n)-\tilde{x}(n)\right]^2}{\sum_{n=1}^{N}x^2(n)}}, \quad \text{PRDN, [\%]} = 100\sqrt{\frac{\sum_{n=1}^{N}\left[x(n)-\tilde{x}(n)\right]^2}{\sum_{n=1}^{N}\left[x(n)-\bar{x}\right]^2}},$$

where $x(n)$ and $\tilde{x}(n)$ are the samples of the original and the reconstructed signals, respectively, $\bar{x}$ – the mean value of the original signal, and N – the length of the window over which the PRD is calculated.

For compression evaluation we used the compression rate (CR) defined as the ratio between the number of bits needed to represent the original and the compressed signal,

$$\text{CR} = \frac{b_{\text{orig.}}}{b_{\text{comp.}}},$$

where $b_{\text{orig.}}$ and $b_{\text{comp.}}$ represent the number of bits required for the original and compressed signals, respectively.

For global evaluation we used the Quality Score (QS) introduced by Fira *et al.*, (2008), which represents the ratio between the CR and the PRD.

4. Experimental Results

We used 24 ECG recordings from the MIT-BIH Arrhythmia database acquired at a sampling frequency of 360 Hz, with 11 bits/sample (MIT BIH). Besides the ECG signals, the database also includes annotation files containing the index of the *R*-wave and the class to which each ECG pattern belongs. These annotations were necessary in the preprocessing stage (segmentation of cardiac cycles and building of dictionaries).

In Table 1 the average results for 24 ECG records from the MIT-BIH Arrthmia database are presented.

Table 1
Average Results for 24 ECG Records

Projection matrix	CR	Avg. PRD	Avg. PRDN	QS
Patient specific dictionary with un-centered *R*-wave				
Gaussian distribution Random*Dict†(20*301)	15:1	0.78	11.98	19.23
0 and 1 (with controlled arrangement) (20*301)	15:1	0.94	16.06	15.87
Gaussian distribution Random (20*301)	15:1	0.82	13.82	18.29
Patient specific dictionary with centered *R*-wave				
Gaussian distribution Random*Dict†(20*301)	15:1	0.51	9	29.13
0 and 1 (with controlled arrangement) (20*301)	15:1	0.71	12.4	20.98
Gaussian distribution Random (20*301)	15:1	0.72	12.51	20.59

Since many authors report besides the average results obtained on the MIT-BIH databases also the results on record no. 117 we have presented such results in Table 2.

Table 2
Average Results for the 117 Record

Projection matrix	CR	Avg. PRD	Avg. PRDN	QS
Patient specific dictionary with un-centered *R*-wave				
Gaussian distribution Random*Dict†(20*301)	15:1	0.38	8.82	39.47
0 and 1 (with controlled arrangement) (20*301)	15:1	0.56	12.81	26.78
Gaussian distribution Random (20*301)	15:1	0.53	12.27	28.30
Patient specific dictionary with centered *R*-wave				
Gaussian distribution Random*Dict†(20*301)	15:1	0.38	8.73	39.47
0 and 1 (with controlled arrangement) (20*301)	15:1	0.49	11.25	30.61
Gaussian distribution Random (20*301)	15:1	0.48	11.15	31.25

In Table 3 we present results for reconstructed cardiac patterns with and without centered *R*-wave for CR = 4:1, 10:1 and 15:1 for Gaussian distribution Random*Dict† projection matrix.

Table 3
*Average Results for the 117 Record for CR = 4:1, 10:1, Respectively 15:1 and Matrix Projection by Type Gaussian Distribution Random*Dict†*

Projection matrix	CR	Avg. PRD	Avg. PRDN	QS
Patient specific dictionary with un-centered *R*-wave				
Gaussian distribution Random*Dict†	4:1	0.19	4.36	21.05
	10:1	0.29	6.77	34.48
	15:1	0.38	8.82	39.47
Patient specific dictionary with centered *R*-wave				
Gaussian distribution Random*Dict†	4:1	0.19	4.54	21.05
	10:1	0.29	6.80	34.47
	15:1	0.36	8.43	41.66

Table 4 contains the average results for 24 records from the database and also record no. 117 reported by Polania *et al*., (2011a, b) and Mamaghanian *et al*., (2011).

Table 4
Other results for Average Values for 24 Records and 117 Record

	Record / Ave.	CR	Avg. PRD	Avg. PRDN
Other Compression Algorithms				
POLANIA (Polania *et al*., 2011a,b)	117	8:1	2.18	Notspec.
POLANIA [Polania et al. 2011a,b]	117	10:1	2.5	Notspec.
MAMAGHANIAN (Mamaghanian *et al*., 2011) for before and after inter-packet redundancy removal and Huffman coding	Aver. for 24 records	4:1 (75)	Before Huffman 35	
			After Huffman 15	
		10:1 (90)	Before Huffman >45	
			After Huffman >45	
		15:1 (93)	Before Huffman >45	
			After Huffman >45	

Note that Mamaghanian *et al*., (2011), present a compression method based on the classic CS followed by Huffman coding. Thus the final CR is increased by using Huffman coding. The results obtained by Mamaghanian *et al*., (2011), are presented both before and after Huffman coding. Therefore, for a relevant comparison our results should be compared to those before Humman coding reported by Mamaghanian *et al*., (2011).

Note also that Mamaghanian uses the compression ratio expressed as

$$\mathrm{CR} = \frac{b_{\text{orig.}} - b_{\text{comp.}}}{b_{\text{orig.}}} \cdot 100,$$

that is different from the formula used by us in this paper. Therefore, in Table 5 we presented the same number of bits required for the original and compressed signals difference between the two formulas, used, by Mamaghanian (Mamaghanian *et al.*, 2011) and by us in this paper.

Table 5
Correspondence between CR Used by Mamaghanian (Mamaghanian et al., 2011) and us in this Paper

$\mathrm{CR}=\frac{b_{\text{orig.}}-b_{\text{comp.}}}{b_{\text{orig.}}}\cdot 100$ used by Mamaghanian		$\mathrm{CR}=\frac{b_{\text{orig.}}}{b_{\text{comp.}}}$ used by us in this paper	
Mamaghanian	in this paper	Mamaghanian	in this paper
10	1.11	91	11.11
20	1.25	92	12.50
30	1.43	93	14.29
40	1.67	94	16.67
50	2	95	20
60	2.5	96	25
70	3.33	97	33.33
80	5	98	50
90	10	99	100

4. Conclusions

In this paper we propose a new ECG compression method based on the CS concept which, on one hand requires an ECG signal preprocessing to delimitate the ECG signal in cardiac cycles (heart beat or cardiac patterns) to be compressed and, on the other hand, speculates the ECG signal specific features of each patient in the construction of the dictionary. Three projection matrices needed for compression, *i.e.*, a projection matrix built taking into account the dictionary that will be used in the reconstruction phase (decompression), a Bernoulli matrix type, and a Gaussian random matrix are analysed.

It is apparent that the best QS has been obtained for the method using patient specific dictionary with centered *R*-wave and optimized projection matrix. The results of Gaussian projection matrix are close to matrix with 0 and 1 (with controlled arrangement).

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ACHIZIȚIE COMPRIMATĂ A SEMNALELOR ECG UTILIZÂND DICȚIONARE SPECIFICE PACIENTULUI

(Rezumat)

Se propune o nouă metodă de compresie a semnalelor ECG bazată pe conceptul de Achiziție Comprimată, metodă care, pe de o parte necesită o preprocesare a semnalului ECG pentru segmentare în cicluri cardiace care urmează a fi comprimate şi, pe de altă parte, speculează proprietățile specifice ale ECG a pacientului în construcția dicționarului. Au fost utilizate trei tipuri de matrice de proiecție, una bazată pe utilizarea dicționarului care va fi utilizat în faza de reconstrucție, o matrice de tip Bernoulli şi una aleatoare Gaussiană. Cele mai bune rezultate s-au obținut cu dicționare cu unda *R* centrată şi matrice de proiecție optimizată. Rezultatele obținute cu matrice de proiecție Gaussiene sunt apropiate de cele bazate pe matricea conținând 0 şi 1 cu aranjare controlată.