Compressed Sensing and Classification of Cardiac Beats using Patient Specific Dictionaries

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Keywords: ECG, Compressed Sensing, Classification.

Abstract: In this paper, we investigated the benefits of compressed acquisition for monitoring applications of patients with various heart diseases. The possibility of heartbeat acquisition followed by classification into one of two classes, namely, normal beats or pathological has been approached using patient-specific dictionaries. Moreover, 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) have been compared. The dictionaries used in the reconstruction phase were built with and without centred R waves.

1 INTRODUCTION

Based on the concept of signal sparsity in terms of the atoms of a certain dictionary and making use of classical decomposition algorithms the literature of the latest years proposes and investigates the interesting possibility of joining signal acquisition and compression within the concept of compressed sensing [Donoho 2006, Donoho 2004, Candes 2008]. It has been mathematically proved that if a class of signals allow a representation in terms of a small number of components in a properly selected base (i.e., the signal is "sparse" in that specific base or with respect to the atoms of a dictionary), the signals can be reconstructed with a very good precision from a reduced number of measurements consisting of projections on random vectors by solving a linear programming problem.

The decomposition of a signal in terms of an over-complete dictionary it is not unique, and can be obtained by means of general methods such as method of frames (MOF), matching pursuit (MP) and methods based on special dictionaries, such as, the best orthogonal basis (BOB) or basis pursuit (BP) [Elad 2007, Shaobing Chen 1998, Polania 2011, Zhang 2013].

2 BACKGROUND ON COMPRESSED SENSING

Compressed sensing is a new concept in signal processing basically consisting in minimizing the number of measurements / projections to be taken from signals that are sparse while still retaining the information necessary to approximate them well.

Consider a family of signals $x_j \in R^n$ known to have sparse representations using at most T atoms from a fixed dictionary $D \in R^{nxk}$. Such signals can be described as

$$\forall j, \quad x_j = D\alpha_j \tag{1}$$

with $\|\alpha_j\|_0 \le T << n$ where T is the sparsity of the signals and the l_0 – norm counts the number of non-zeros entries in α_j.

Compressed sensing consists of a joint sensing and compression for such signals. Using a projection matrix $P \in \Re^{pxn}$ with $T < p << n$, the technique of compressed sensing seeks to represent x_j by p scalars y_j given by

$$y_j = Px_j \tag{2}$$

Fira, M., Goras, L., Maiorescu, V-A. and Luca, M.
Compressed Sensing and Classification of Cardiac Beats using Patient Specific Dictionaries.
In *Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2016)*, pages 173-179
ISBN: 978-989-758-180-9

The original signal x_j can be reconstructed from y_j by exploiting the sparsity of it is representation so that among all possible α satisfying

$$y_j = PD\alpha \tag{3}$$

we seek the sparsest. If this representation coincides with α_j, we get a perfect reconstruction of the signal using equation 3.

$$x_j = D\alpha_j \tag{4}$$

In general this reconstruction is based on the solution of

$$\min_{\alpha} \|\alpha\|_0 \quad y_j = PD\alpha \tag{5}$$

which is known to be NP – hard even for moderate-sizes of the linear system of the constraints.

Reconstruction algorithms are standard linear programming algorithms with perhaps quadratic constraints such as LARS, LASSO, SparseLab, l1Magic, (Orthogonal) Basis Pursuit, (Orthogonal) Matching Pursuit etc.

2.1 Compressed Sensed and Key Problems

A key problem in CS is the choice or the construction of the dictionary based on which the compressed signal reconstruction is made. For many classes of signals, dictionaries (time-frequency or time-scale dictionaries) based on which good results using the CS concepts have been obtained are already known. Still, there are classes of signals for which the use of standard dictionaries do not ensure spectacular compression results, due to the fact that the sparsity of these signals is not ensured. This signal classes may require the construction of new dictionaries to fit new types of data features. The analytic construction of dictionaries such as wavelets or curvelets stems from deep mathematical tools from Harmonic Analysis. It may however be difficult and time consuming to develop complex mathematical theory each time a new class of data, which requires a different type of dictionary, is met. An alternative solution is dictionary learning, which aims deduction the dictionary from a set of training data [Fira 2010]. Dictionary learning, also known as sparse coding, has the potential of 'industrialising' sparse representation techniques for new data classes.

Recent articles present the possibility of combining the concepts of signal representation using dictionaries with signal classification concepts, solving the classification problems based not on the concrete signal, but on a small number of random measurements of the signal acquired using a random projection matrix. Generally speaking, the results of the classifications are influenced by two important factors, namely the modality of constructing the dictionary and the classifier used.

The possibility of classifying compressed signals is extremely useful because it brings additional information about the signal, information that will allow the reconstruction of original signals using specific dictionaries. In compressed sensing, in case the sparsity of the signal cannot be ensured using a single general dictionary, the use of specific dictionaries will lead to a decrease of the reconstruction error.

Starting from the mathematic fundaments of compressed sensing, we aimed at the software implementation of the compressed sensing for ECG medical signals. The key element that appears in the case of this type of signals is to find a dictionary that would ensure the ECG signals sparsity in direct connection to the reconstruction method.

2.2 Purpose and Objectives

Based on the results of the classification of acquired heart rate compressed presented [Fira 2011a] and the results for the patient-specific dictionaries presented in [Fira 2011 b, Fira 2013], in this paper, we propose a new method that combines the above previous approaches. The aim is to develop and implement a method for compressed sensed of ECG signal together with the detection of the abnormal heart beats and transmission of these beats to a center for monitoring of people with heart diseases. The proposed problem to solve is divided into the following sub-problems:

- Construction of patient-specific dictionaries;
- Heartbeat classification;
- Compressed acquisition of abnormal heart beats;
- Transmission of abnormally beats to a surveillance center / recording of these beats for further investigation by qualified personnel;
- Reconstruction of compressed sensed beats.

3 METHOD

Starting from ECG signals for which the position of the R-wave is known exactly, we segment the ECG signals in heart beats cycles. : A cardiac pattern begins from the middle of an RR interval and finishes at the middle of the next RR interval [Fira

2010]. Then, based on the ECG signal segmented in cardiac cycles, we have developed two methods of building patient-specific dictionaries, namely:

- Dictionary consisting in heart beats with centered R wave;
- Dictionary with not centered R Wave.

3.1 Dictionaries Built from Cardiac Beats with Centred R Wave

Each segment contains the P-wave, the QRS complex and the T-wave and each cardiac segment thus obtained was resampled at 301 samples so that, after that all patterns will have the same dimension, thus being possible to create a specific dictionary for the ECG signals. To obtain cardiac patterns with resampling and centred R wave, after segmentation the peak of the R wave was positioned on sample 151 and then the whole beat was resampled such that on the right and on the left of the R peak there will be 150 samples i.e., the R wave will be positioned in the middle.

NOTE: The resampling operation of the cardiac segment on 301(150 samples on each side of the R wave), which has as purpose to obtain cardiac patterns with the same size, is a reversible modification, as long as the information related to the initial dimension is maintained.

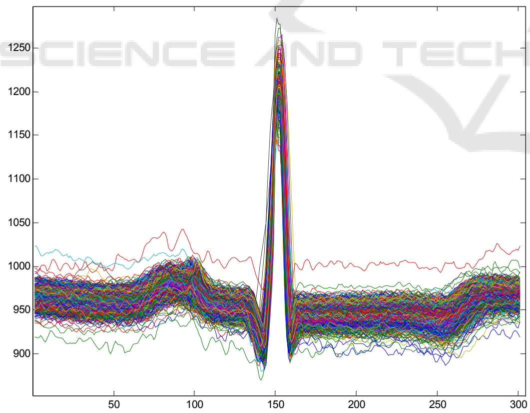

Figure 1: Cardiac beat with centred R wave.

3.2 Dictionaries Built from Cardiac Beats without Centred R Wave

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

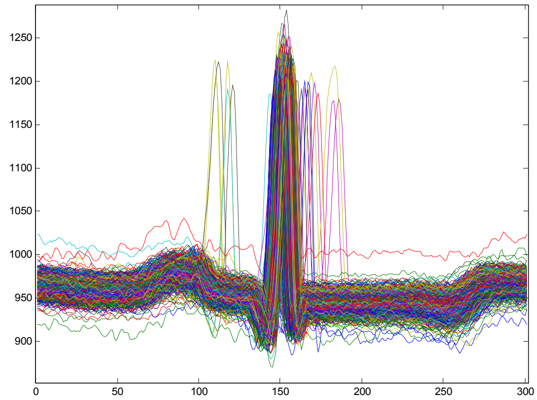

Figure 2: Cardiac beat without centred R wave.

3.3 Projection Matrices

It is known that the acquisition results are influenced to some extent also by the type of matrix used for acquisition. Therefore we analyzed the influence of the compression matrix on acquisition and on the classification of the compressed heartbeats, testing three types of matrices, namely:

- Random matrix
- Bernoulli matrix
- Optimized matrix depending on dictionary [Cleju 2011] - (product of random matrices and the dictionary transposed)

3.4 KNN - k-Nearest Neighbours

The classifier used for heart beats classification is of k-Nearest Neighbors (kNN) type. We opted for this type of classifier since it is simple to implement in practical applications even in hardware. For improved results one can choose more complex classifiers, but the results offered by this classifier proved to be good enough; as a consequence we selected it even for future hardware implementations.

The kNN classifier was trained with normal and abnormal heart beats evenly distributed on both classes. The beats used to train the classifier were extracted from the dictionary constructed for the compressed acquisition.

3.5 Cardiac Patterns Reconstruction

For reconstructing the patterns we use the Basis Pursuit algorithm to determine the coefficients. The reconstruction of the compressed cardiac patterns is based on using the above discussed patient specific dictionary with or without centred R-wave. The

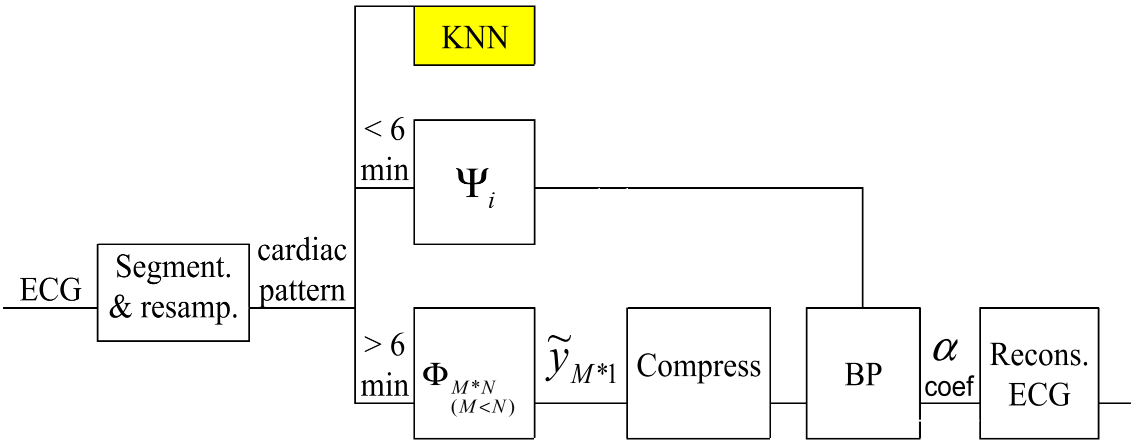

Figure 3: Principle of the method.

patient specific dictionary consists of 700 cardiac patterns.

3.6 Principle of the Method

Most of the methods proposed by different authors do not capitalize the quasi periodic nature of the ECG signal and the specific particularities of the patient. Therefore, in this paper, we propose a method that takes into account both advantages, namely, working with heart beats (not with the ECG signal as it is recorded) and secondly, the used dictionaries are made of cardiac cycles taken from the subject of acquisition. Thus, the first six minutes of registration or previous recordings from the same subject (if any) are used to build the dictionary needed for reconstruction. Only after the dictionary was built, the compressed sensing of the heart beats starts, followed by the classification in normal or pathological for each heartbeat and then the transmission or storage of data when an abnormality is detected.

For the implementation of the proposed method a buffer memory is necessary. 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. When using segments with no R wave alignment, the extracted segments are also subsequently resampled to 301 samples. As already shown, for R wave centred, 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.

A block diagram of the proposed method is shown in Figure 3.

3.7 Validation of the Compression Method

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:

$$PRD\,\% = 100\sqrt{\frac{\sum_{n=1}^{N}(x(n)-\tilde{x}(n))^2}{\sum_{n=1}^{N}x^2(n)}} \tag{6}$$

$$PRDN\,\% = 100\sqrt{\frac{\sum_{n=1}^{N}(x(n)-\tilde{x}(n))^2}{\sum_{n=1}^{N}(x(n)-\bar{x})^2}} \tag{7}$$

where $x(n)$ and $\tilde{x}(n)$ are the samples of the original and the reconstructed signals respectively, $\bar{x}$ is the mean value of the original signal, and N is 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,

$$CR = \frac{b_{orig}}{b_{comp}} \tag{8}$$

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

4 EXPERIMENTAL RESULTS

To test the proposed method ECG segments from 14 ECG recordings (ID 100, 101, 102, 104, 105, 106, 119, 201, 202, 203, 210, 212, 217, 219) from the MIT-BIH Arrhythmia [physionet] database were used. The ECG signals were digitized through sampling at 360 samples per second, quantized and encoded with 11 bits. The MIT-BIH Arrhythmia database, along the ECG signals, also contains annotations of the cardiac beats for each of the recordings.

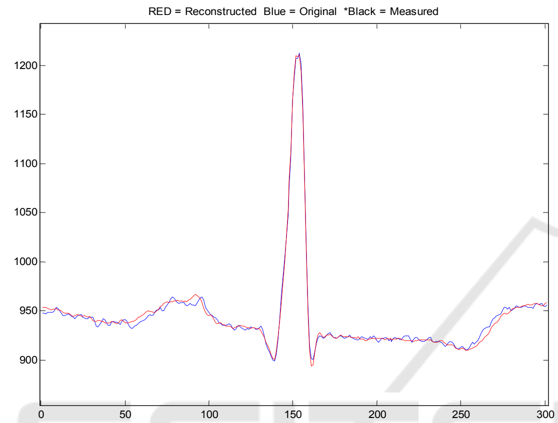

Figure 4: Original and reconstructed cardiac beat.

Table 1 presents the mean results for 14 ECG records for CR = 15:1 and tree types of confusion matrices.

Table 1: Average Results for 14 ECG Records.

Projection matrix	CR	Avg. PRD	Avg. PRDN	Classification rate
Patient specific dictionary with un-centered R-wave				
Gaussian distribution Random*Dict†(20*301)	15:1	0.78	11.98	92.24%
0 and 1 (with controlled arrangement)(20*301)	15:1	0.94	16.06	84.71%
Gaussian distribution Random (20*301)	15:1	0.82	13.82	91.14%
Patient specific dictionary with centered R-wave				
Gaussian distribution Random*Dict†(20*301)	15:1	0.51	9	93.41%
0 and 1 (with controlled arrangement)(20*301)	15:1	0.71	12.4	88.06%
Gaussian distribution Random (20*301)	15:1	0.72	12.51	89.70%

Since many authors report besides the average results obtained on the MIT-BIH databases results on record no. 117 we have presented such results in Table 2. Heart beat rate classification of this record is not calculated because it is not relevant. There are mostly normal heart beats, so a classification in such a situation is senseless.

Table 2: Average Results for the 117 Record.

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

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
Patient specific dictionary with un-centered R-wave			
Gaussian distribution Random*Dict†(20*301)	4:1	0.19	4.36
	10:1	0.29	6.77
	15:1	0.38	8.82
Patient specific dictionary with centered R-wave			
Gaussian distribution Random*Dict†(20*301)	14:1	0.19	4.54
	10:1	0.29	6.80
	15:1	0.36	8.43

Table 4: Average Results for the 100 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	Classification rate
Patient specific dictionary with un-centered R-wave				
Gaussian distribution Random*Dict†(20*301)	4:1	0.19	4.36	99.12%
	10:1	0.29	6.77	98.17%
	15:1	0.38	8.82	98.83%
Patient specific dictionary with centered R-wave				
Gaussian distribution Random*Dict†(20*301)	14:1	0.19	4.54	99.85%
	10:1	0.29	6.80	96.27%
	15:1	0.36	8.43	99.56%

In Table 4 we present results for record no. 100 for reconstructed cardiac patterns with and without centred R-wave for CR = 4:1, 10:1 and 15:1 for Gaussian distribution Random*Dict† projection matrix and for classification witk KNN.

Table 5: Results for ECG Records for compression ratio CR= 15:1 and centred R wave.

PPV_ class1%	PPV_ class2%	k-Nearest Neighbors	ID_ ECG	Total Classification rate %
99.9	96.4	1	100	99.8
99.9	85.7	2		99.6
99.6	92.9	3		99.4
88.8	100.0	1	101	88.8
99.4	100.0	2		99.4
96.4	100.0	3		96.4
100.0	99.5	1	102	99.5
100.0	97.6	2		97.6
100.0	97.7	3		97.7
68.8	99.1	1	104	98.0
75.0	96.9	2		96.2
56.3	99.8	3		98.2
95.4	87.5	1	105	95.3
98.2	87.5	2		98.1
97.5	87.5	3		97.4
99.6	97.7	1	106	98.9
99.9	95.7	2		98.4
99.9	95.7	3		98.4
100.0	100.0	1	119	100.0
100.0	100.0	2		100.0
100.0	100.0	3		100.0
51.4	83.5	1	201	59.0
65.7	77.1	2		68.4
61.3	79.9	3		65.7
49.3	80.0	1	202	50.3
66.2	75.0	2		66.5
57.5	80.0	3		58.2
97.3	94.8	1	203	50.3
98.6	90.5	2		66.5
97.7	94.4	3		58.2
98.7	93.3	1	210	98.2
99.6	87.7	2		98.5
99.2	89.0	3		98.3
97.2	100.0	1	212	99.0
98.4	99.7	2		99.2
96.9	100.0	3		98.9
0.0	100.0	1	217	82.9
0.0	100.0	2		82.9
0.0	100.0	3		82.9
90.0	62.9	1	219	89.3
99.3	54.3	2		98.1
93.8	60.0	3		92.8

The positive predictive value (PPV) is defined as

$$PPV = \frac{TP}{TP + FP} \tag{9}$$

where a "*true positive*" (TP) is the event that the test makes a positive prediction, and the subject has a positive result under the gold standard, and a "*false positive*" (FP) is the event that the test makes a positive prediction, and the subject has a negative result under the gold standard.

Table 6 contains the average results for 14 records from the database and also record no. 117 reported in [Polania et al. 2011a, b] and [Mamaghanian et al. 2011].

Table 6: Other results for Average Values for 24 Records and 117 Record.

	Record / Ave.	CR	Avg. PRD	Avg. PRDN
Other Compression Algorithms				
POLANIA [Polania 2011a,b]	117	8:1	2.18	Notspec.
POLANIA [Polania 2011a,b]	117	10:1	2.5	Notspec.
MAMAGHANIAN [Mamaghanian 2011] for before and after inter-packet redundancy removal and Huffman coding	Ave. for 14 recs	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 in [Mamaghanian 2011] presents a compression method followed by Huffman coding. Thus the final CR is increased by using Huffman coding. In [Mamaghanian 2011] results are presented both before and after Huffman coding. Therefore, for a relevant comparison our results should be compared to those before Humman coding reported in [Mamaghanian 2011].

Moreover, in the above work the compression ratio expressed as

$$CR = \frac{b_{orig} - b_{comp}}{b_{orig}} * 100 \tag{9}$$

that is different from the formula used in this paper.

In Table 7 we presented the number of bits required for the original and compressed signals difference between the two formulas used Mamaghanian in [Mamaghanian 2011] and by us in this paper.

Table 7: Correspondence between CR used in [Mamaghanian 2011] and in this paper.

$CR = \frac{b_{orig} - b_{comp}}{b_{orig}} * 100$ **used by Mamaghanian**		$CR = \frac{b_{orig}}{b_{comp}}$ **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

5 CONCLUSIONS

In this paper the possibility to build and use patient-specific dictionaries for compressed sensing heart beats that are classified by a KNN type classifier as normal and abnormal. The presented principle has several significant features, namely:

• gives very good results for the classification in two classes (normal and abnormal), i.e., detection of abnormal compressed sensed heartbeats

• allows reconstruction for the compressed sensed heartbeats

• needs few calculations in the compressed acquisition stage

• uses a k-NN type classifier for the classification stage, which also implies less complex calculations.

Taking into account all these aspects, this work can be considered relevant for a first step in the implementation of an algorithm for monitoring and management of cardiac crisis situations.

ACKNOWLEDGEMENTS

This work was supported by a grant of the Romanian National Authority for Scientific Research and Innovation, CNCS – UEFISCDI, project number PN-II-RU-TE-2014-4-0832 "*Medical signal processing methods based on compressed sensing; applications and their implementation*"

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