ECG COMPRESSED SENSING BASED ON CLASSIFICATION IN COMPRESSED SPACE AND SPECIFIED DICTIONARIES

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ABSTRACT

An electrocardiographic signal (ECG) compressed sensing (CS) method, its reconstruction using specific dictionaries of cardiac pathologies and method evaluation testing using classical measures as well as by classification error of the reconstructed patterns based on the K-Nearest Neighbour classifier (KNN) are presented. For compressed sensing, a random matrix with standard normal distribution was used, followed by a classification of compressed signals in one of eight possible pathological classes. For each class a specific dictionary was created, and the signals were reconstructed using the Basis Pursuit algorithm according to the result of the classification.

1. INTRODUCTION

The processing techniques of medical signals generally consist of standard algorithms for signals processing. One of the methods recently presented in the specific literature related to medical signals, is centred on the representation of the signals according to a dictionary/basis of representation. Starting from this idea, the modality of dictionary construction, finding the optimal dictionary/basis and the signal mode of representation with respect to the dictionary are complex problems, intensely studied and presented in the literature. For example, for each of the previously mentioned sub-issues, there is no unique or optimal solving algorithm, knowing the fact that each algorithm has a series of advantages and limitations. This is why, according to the nature of the medical signal and the intended application, an appropriate solving solution for the sub-issues mentioned above should be chosen.

The overall performance of a compression algorithm depends on the balance of three important characteristics: the compression rate (CR) defined as the ratio between the number of bits needed to represent the original and the compressed signal, the reconstruction error and the computational complexity, the first two being strongly interdependent.

The following considerations are based on the results obtained by renowned researchers such as E. Candes [1], Elad [2], D. Donoho [3,4], J. Romberg [5] and J. Burgain , in the field of signal acquisition, analysis, compression and processing. The goal of these research is that of finding an optimal representation for a signal in a different space or according to a dictionary, to find means of obtaining an optimal encoding from random projections, and to determine the conditions in which these methods are possible.

This paper presents an ECG signal CS method based on specific dictionaries and techniques of sparse decomposition. Using a training set of ECG signals characteristic to both normal behaviour and several cardiac diseases, a method of constructing over-complete dictionaries is presented. Based on these dictionaries and classification of compressed signals (nearest neighbor type supervised classifier) in one of the eight classes, an ECG signal can be represented as a sparse combination of a few significant atoms. CS theory ensures that in this case, the signal can be reconstructed from a small number of random projections using linear programming algorithms.

The reconstruction results of the proposed method are evaluated with standard measures such as the compression rate (CR), the percentage root-mean-square difference (PRD) and the Quality Score (QS) as well as by the rate of classification of the reconstructed signals in one of the eight possible classes. In this way both a quantitative and a qualitative (which is as relevant, but more easily interpreted from the viewpoint of a specialist physician) evaluations are available.

In lossy compression techniques, the problem of defining the error criterion for evaluating the distortion between the reconstructed signal and the original signal one is of paramount importance, particularly for biomedical signals like the ECG, where a slight loss or change of information can lead to wrong diagnostics. Most ECG compression algorithms in the literature evaluate the errors using the percentage root-mean-square difference (PRD) measure defined as

$$PRD\% = 100\sqrt{\sum_{n=1}^{N}(x(n)-\tilde{x}(n))^2 \Big/ \sum_{n=1}^{N} x^2(n)}$$

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

Zigel [6] introduced a new measure, not always easy to use, called Weighted Diagnostic Distortion (WDD) which consists in comparing the P and T wave, and QRS complexes features of the two ECG signals, to evaluate the relative preservation of the diagnostic information in the reconstructed signal compared to the original one.

Moreover, the QS [17] representing the ratio between the CR and the PRD has been recently proposed as a performance measure that takes into consideration the trade-off between CR and distortion.

2. PRINCIPLES OF COMPRESSED SENSING

The concept of compressed sensing [1], [5], [7] refers to the possibility of reconstructing signals which are sparse in certain bases or dictionaries from a reduced number of projections on a set of random vectors. It seeks to answer the question "how can we achieve an efficient compression?" using the principle "acquire in the most economic way, ask questions later".

The technique is attractive in order to decrease the acquisition and transmission resources at the price of increasing those for decoding for which there are no computation constraints.

In its standard form, for the 1D case the theory of CS considers signals x belonging to R^N which are K-sparse or compressible in some basis $\Psi = \{\Psi_i, i = 1,...,N\}$ i.e. they can be written as $x = \Psi\alpha$ where the elements of $\alpha = \{\alpha_i, i = 1,...,N\}$ are rapidly decreasing to zero, the signals being well enough approximated using only the K largest coefficients ($K<N$). In CS theory it has been proved that such a signal can be recovered from a (small) number of order $M = O(K\log(N/K))$ (M is proportional to $K\log(n/K)$) of non-adaptive projections on a set of random vectors with an error of the same order as the error obtained by truncating the N-K non-significant coefficients to zero [8-9].

For sparse signals, instead of acquiring N samples according to the sampling theorem, a smaller number M of signal independent projections on random vectors are taken, from which the signal can be rebuilt. The $M\times 1$ projection vector y can be written

$$y = \Phi x + n = \Phi\Psi\alpha + n = \Theta\alpha + n$$

where the signal n represents the cumulated effect of the quantification and of the inherent noise of the measurement. This is an undetermined equation system, with an infinite number of possible solution vectors α; thus it is not straightforward to solve and find the original signal [18]. However, CS theory shows that there is a single sparse–enough solution α; as the original signal x is known to have been sparse, it follows that the sparsest α must be the coefficient vector of the original signal.

Thus the reconstruction of the signal amounts to finding the sparsest decomposition α of the measurement vector in the dictionary Θ.

This is an optimization problem which can be approximately solved with a variety of greedy algorithms or with standard linear programming algorithms, such as Basis Pursuit, Matching Pursuit, Orthogonal Matching Pursuit etc., for which there are fast implementations.

Since CS theory is very efficient provided the signals are highly sparse in an orthogonal basis – a property which is seldom satisfied – it has been extended to the case of signals that are sparse with respect to over-complete dictionaries, i.e., dictionaries whose elements (atoms) are not linearly independent [10].

Again the signal x can be written as $x = \Psi\alpha$, where now Ψ is an $N\times P$ matrix with P>>N. Several choices for over-complete dictionaries are: joined dictionaries obtained by merging complete dictionaries (i.e., Fourier + canonical basis, Fourier + wavelet), wavelet over-completes dictionaries, optimized/learned over-complete dictionaries etc.). For these cases the previously mentioned methods work just as well, in particular the BP (basis pursuit) method. The method finds the best representation of a signal by minimizing the l_1-norm [3] of the decomposition coefficient vector, i.e.,

$$\text{minimize} \quad \|\alpha\|_1 \quad \textit{subject to}\ \Psi\alpha = x$$

where the non-zero components of α correspond to the dictionary atoms which are used in the signal representation. The BP algorithm converts the above minimization problem into an equivalent double sized linear programming problem (LP) of the form:

$$\text{minimize} \quad c^T\beta \quad \textit{subject to}\ \Psi\beta = x, \quad \beta \in R^{2N}, \beta_i \geq 0$$

where $c^T\beta$ is the objective function and $\Psi\beta = x$ can be viewed as a collection of constraints.

Linear programming has been extensively studied in literature, and many algorithms exist for solving such problems; in this paper the Interior Point Method has been chosen.

3. METHOD

The key issue regarding an efficient compressibility for a class of signals is that of finding appropriate dictionaries and projection matrices to get high compression QS's. For example, for many classes of signals, good dictionaries for CS have been already proposed [11], [12], [13]. Even so, there are classes of signals like the ECG for which the use of standard dictionaries does not ensure spectacular CS results, thus new dictionaries are needed. The analytic construction of dictionaries such as wavelets, curvelets etc. stems from the deep mathematical tools of Harmonic Analysis [14] [15]. However, since it is difficult and time consuming to develop complex mathematical theory for each class of data, the alternative solution of dictionary learning which consists in building the dictionary from a set of training data is the most advantageous solution.

Considering the example of compressed sensing of ECG signals using a Coiflet4 type wavelet over-complete dictionary, it has been found that for compression ratios greater then 4:1 both the reconstruction errors and the visual inspection were unacceptable [16].

CR = 4:1; PRD = 0.58 ;	CR = 6:1; PRD = 0.80;
CR = 8:1; PRD = 1.02;	CR = 10:1; PRD = 1.51;

As mentioned in [16], the weak results obtained with over-complete wavelet dictionaries for CR over 4:1 have lead to adopting an ECG signal specific dictionary construction method based on cardiac patterns.

In the following we propose a new compressed sensing scheme for cardiac patterns: the signal is slightly pre-processed then it is compressively sensed using a number of projections on random vectors, the new signal thus obtained being then classified in one of the eight classes using the nearest neighbour algorithm (*k-NN*).

Once the compressed signal is classified, the reconstruction of the initial cardiac pattern with the basis pursuit algorithm can be made using the classification information and the specific dictionary for that class.

We used 24 ECG recordings from the MIT-BIH Arrhythmia database acquired at a sampling frequency of 360Hz, with 11 bits / sample. 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.

From the database annotations eight major pattern classes were emphasised, one class of normal cardiac beats and seven classes of pathological beats: atrial premature beat, left bundle branch block beat, right bundle branch block beat, premature ventricular contraction, fusion of ventricular and normal beat, paced beat, fusion of paced and normal beat.

Figure 1 shows the principle of our approach.

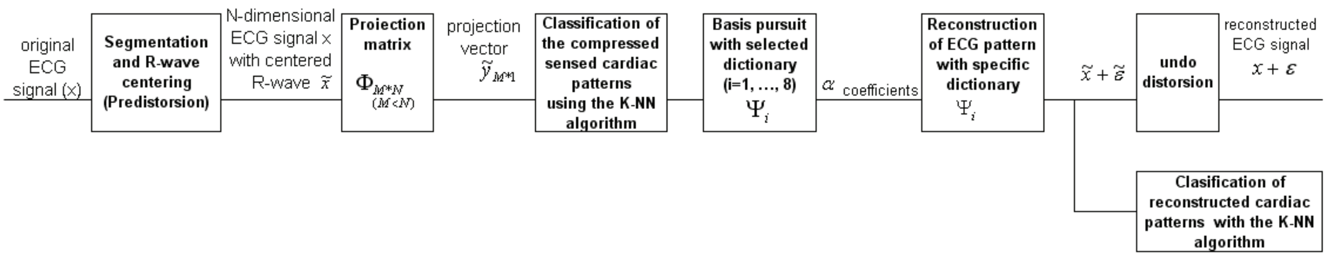

Figure 1 – Principle of the proposed compression/classification/reconstruction system

The compressed sensing. The samples of the ECG are stored in a buffer, then the maxima of the R waves are detected and full cardiac beat cycles consisting of the samples between the midpoints of consecutive RR intervals are formed. Afterwards the R wave is centred by resampling to a fixed number of samples [17] such that all patterns are R-aligned cardiac patterns and have the same size. In our investigations we have used patterns of 301 samples with the R wave positioned on the 150-th sample. The above segmented waves are compressed using a random Gaussian projection matrix. In our case the matrix size was 20x301, equivalent to a compression ratio of 15:1.

The classification of the compressed acquired cardiac beats aims at determining the class of patterns the compressed pattern belongs to. Using 2000 cardiac patterns randomly selected from all eight classes mentioned earlier as a training set for the K-NN algorithm, we classified new compressed sensed cardiac patterns in one of the 8 classes.

The reconstruction of the compressed cardiac patterns is based on using a specific dictionary for each cardiac pattern class (i.e. eight dictionaries in all). Each specific dictionary is composed of 650 cardiac patterns with centred R-wave of the specified class stored as 301*650 matrices. Once the previous block has determined the class to which the signal is supposed to belong, we use the dictionary of that class and the compression projection matrix in the Basis Pursuit algorithm to determine the reconstruction coefficients. Thus, out of the eight dictionaries for the eight cardiac pattern classes, only the dictionary of the determined class is used in the reconstruction process.

To validate the compression we have evaluated the distortion between the original and the reconstructed signals by means of the PRD. Moreover, to estimate the classification ratio of the signals into one of the eight possible classes, we used a KNN classifier to evaluate the reconstructed patterns. The KNN was trained with the patterns (each pattern has 301 samples) contained in these eight specific dictionaries and tested with the reconstructed patterns.

4. RESULTS

To evaluate the proposed compression method we computed the reconstruction distortions (expressed as PRD) and the classification rate of the reconstructed signals using the nearest-neighbour principle. These two measures that we used to validate the method were computed for a compression ratio of 15:1.

4.1 Quantitative distortion estimation using PRD

For testing we have used 50 cardiac patterns out of each pattern class, randomly chosen from the 24 ECG recordings; the cardiac patterns used in the dictionaries were different from those used for testing.

4.4. 1 Classification of compressed cardiac patterns

Using a training database with a number of 2000 cardiac patterns, uniformly distributed over the eight classes and using the K-NN classification algorithm, we obtained a classification accuracy of 93.77%.

Table 1 – Confusion matrix for KNN classification of the compressed patterns with random projection matrix

	class1	**class2**	**class3**	**class4**	**class5**	**class6**	**class7**	**class8**
class1	**96**	2	0	2	0	0	0	0
class2	4	**90**	0	0	2	4	0	0
class3	0	0	**100**	0	0	0	0	0
class4	2	0	0	**98**	0	0	0	0
class5	0	2	0	0	**92**	6	0	0
class6	0	10	2	0	4	**80**	0	4
class7	0	0	0	0	0	0	**100**	0
class8	0	4	0	0	0	0	0	**96**

4.4. 2 Reconstruction based on specific dictionaries

In order to use class-specific dictionaries for reconstruction, the determination of the class to which the compressed pattern belongs is necessary. The correctness of this classification will significantly influence the reconstruction results. Once the class is determined, we used the specific dictionary of that class together with the known projection matrix in the Basis Pursuit algorithm to obtain the reconstruction coefficients. Figure 2 presents one example for each of the eight pattern classes; both the original signal and the reconstructed signal using the class-specific dictionaries are depicted.

Using class-specific dictionaries for the reconstruction a classification accuracy of 93.77%, and an average distortion of PRD = 0.87 were obtained. For a hypothetical 100% correct classification rate, the obtainable average distortion would be PRD = 0.83.

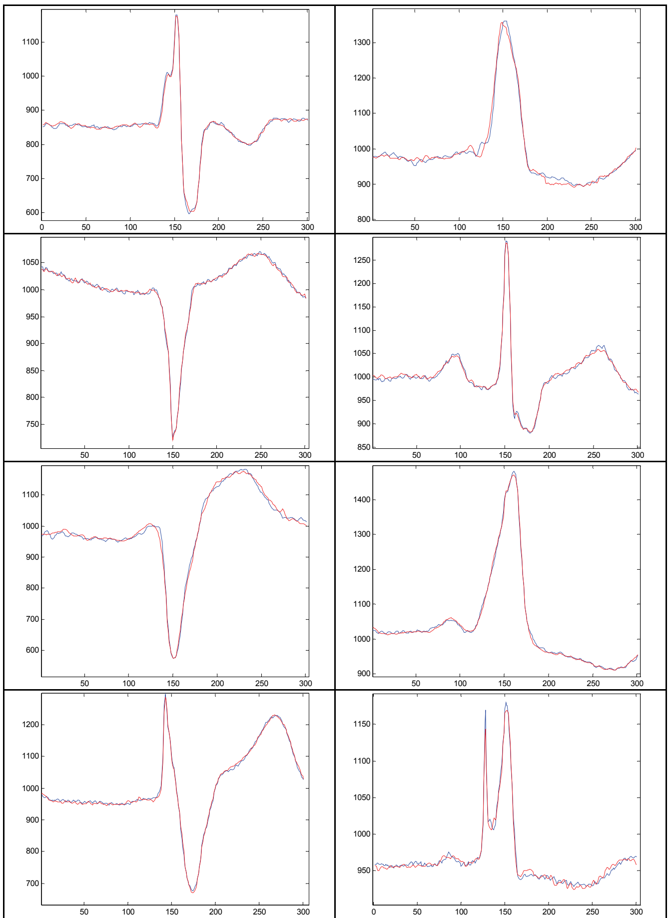

Figure 2 – Original and reconstructed signals with specific dictionaries

4.2 Qualitative estimation of the reconstructed signals based on classification

For a supplementary verification of the quality of the proposed compression scheme, we ran a classification of the reconstructed patterns with the K-NN algorithm. We used the same training data for the classifier, ie 2000 of patterns from all 8 classes, uniformly distributed. To check the classification performance we initially tested the original patterns (i.e. the uncompressed patterns that we used to test the compression scheme). On these patterns we obtained a correct classification rate of 91.77%. In the following we present the results obtained for classifying the reconstructed patterns (400 patterns altogether, 50 from each class).

Table 2 – Confusion matrix for KNN classification of the reconstructed patterns with class-specific dictionaries

	class1	**class2**	**class3**	**class4**	**class5**	**class6**	**class7**	**class8**
class1	**94**	4	0	0	0	0	0	2
class2	4	**88**	0	0	0	4	0	4
class3	0	0	**98**	0	0	2	0	0
class4	0	0	0	**100**	0	0	0	0
class5	8	2	4	0	**84**	2	0	0
class6	0	6	4	0	4	**82**	0	4
class7	0	0	0	0	0	0	**100**	0
class8	0	8	0	0	0	0	4	**88**

The results we obtained with the proposed method are compared in Table 3 with the results of other compression methods in the literature.

Algorithm	**Average of errors**	**Average of CR**	**QS**
Wavelet [19]	18.2 RMS	21.4:1	
SPHIT [20]	3.57 PRD	12:1	3.39
	4.85 PRD	16:1	3.29
	6.49 PRD	20:1	3.08
JPEG2000 [21]	2.19 PRD	12:1	5.47
	2.74 PRD	16:1	5.8
	3.26 PRD	20:1	6.1
QLV – Skeleton – Huffman* [22]	0.641 PRD*	16.9:1*	29.36*
Fira - Skeleton – [18]	1.17 PRD 11.35 RMS	18.27:1	15.61
CS with megadictionary [17]	1.05	15:1	14.28
Proposed method	**0.87 PRD**	**15:1**	**17.24**

Table 3 - Comparison between the proposed method and other compression algorithms for average values for 24 records

NOTE: The results reported in [22] were obtained using a combined ECG compression method consisting of a pre-processing stage with quad level vector (QLV) for the extraction of the ECG skeleton achieving an 8.4:1 compression and a coding block (consisting of delta and Huffman Coding). The results referenced in Table 3 are the final ones improved by the Huffman coding stage.

5. CONCLUSIONS

This paper presents an ECG signal compression method, based on the concept of compressed sensing. For compressed sensing of ECG patterns we used a random projection matrix, with normal distribution. The compressed patterns are classified using the KNN algorithm in one of eight pathological classes: atrial premature beat, left bundle branch block beat, right bundle branch block beat, premature ventricular contraction, fusion of ventricular and normal beat, paced beat, fusion of paced and normal beat. For reconstructing the compressed sensed cardiac patterns we built one specific dictionary for each pathological class separately, and using the basis pursuit algorithm we found the coefficients necessary to represent the compressed signal according to the dictionary atoms. The results of the proposed method are evaluated from a quantitative viewpoint by specific measures (CR and PRD) and from a qualitative viewpoint by the classification of reconstructed patterns using the KNN classifier.

For a CR of 15:1 and with the classification rate of compressed patterns of 93.76%, we obtained for the reconstructed patterns a PRD of 0.87 and a classification rate of 91.77%. For a hypothetical 100% correct classification rate of the compressed patterns, the obtainable average distortion is PRD = 0.83. This result proves that reconstruction errors resulting from using a different dictionary than the one corresponding to the class the original pattern belongs are not significant. This can be explained by the fact that although two patterns belong to different classes, they can have relatively similar waveforms.

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