

# A New Method for Dictionary Matrix Optimization in ECG Compressed Sensing

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**Abstract**—This paper proposes a new method for dictionary matrix optimization with the aim of improving the reconstruction quality of ECG signals delivered by a Compressed Sensing (CS) algorithm. The method exploits the features common to all the records of the ECG signal of the same patient to obtain an optimized dictionary with reduced size. In this way, the signal reconstruction from the compressed samples is performed in a domain defined by a base with a reduced cardinality, thus allowing to increase the signal's reconstruction quality and to reduce the execution time of the reconstruction algorithm. The mathematical model for the patient specific ECG signals dictionary optimization is described, and a preliminary experimental assessment is presented. The obtained results clearly demonstrates that the proposed method exhibits a reconstruction quality in terms of Percentage of Root-mean-squared Difference (*PRD*) lower than a method adopting the non-optimized dictionary matrix.

**Index Terms**—Compressed Sensing, ECG, Dictionary Optimization, Measurement Quality.

## I. INTRODUCTION

Due to the increase in demand for tele-health services, the implementation of telemedicine based healthcare systems is rapidly growing. In particular, Wearable Health Devices (WHD) are an emerging technology that can be used for continuous health monitoring, thus providing real-time information on the patient vital signs and allowing the detection of possible anomalies [1]. These systems can be implemented using the Internet of Things (IoT) paradigm, with small, smart and low power sensors, which are Internet connected [2]–[4]. Usually, these sensors acquire several vital signs, such as: (i) Electrocardiogram (ECG), (ii) blood pressure, (iii) respiratory rate, (iv) hearth rate, and (v) body temperature [1], [5], [6]. The acquired physiological parameters are sent to a *Server* for storage and online data processing, by means of a wireless interface [1]. In case of continuous monitoring (i.e. days, weeks, months), the amount of transmitted data strictly affects the energy consumption of the wearable device. Furthermore, the *Server* requires the use of large memories for the storage of the patients vital signs. In the literature, several data compression techniques have been developed for reducing the number of transmitted and stored data, [7]–[10]. These methods are based on domain transforms which requires a high computational load onboard of the sensor node. Emerging techniques for data compression that overcome this limit are based on the Compressed Sensing (CS) theory, [11]. In this

case, the CS-based methods require low computational power during compression, at the expense of a higher computational load during reconstruction [12]. However, their reconstruction quality is lower than the others, such as [7], [12], [13]. One way to improve the reconstruction quality of ECG signals obtained by CS framework is to use a dictionary matrix tuned on the patient specific ECG signature, [14]–[20].

In this paper, a new method for dictionary matrix optimization for ECG reconstruction is proposed. It has been developed for improving the reconstruction quality of the CS algorithm presented in [21].

The rest of the paper is structured as follows. In Section II, an overview of CS for ECG signals is presented. The proposed dictionary matrix optimization is then reported in Section III, followed by experimental results and performance evaluation in Section IV. Lastly, in Section V, conclusions and future work are drawn.

## II. COMPRESSED SENSING OVERVIEW

CS represents a signal processing framework aimed at acquiring a reduced information set from signals of interest (i.e. in a compressed version of the signal under observation) and at reconstructing its digital version from this information set [11], [13], [21]–[25]. In general, the CS process is described as  $\mathbf{y} = \Phi \cdot \mathbf{x}$ , where  $\mathbf{x} \in \mathbb{R}^{N \times 1}$  is the vector of  $N$  samples of the signal under observation,  $\mathbf{y} \in \mathbb{R}^{M \times 1}$  is the vector of the  $M$  compressed samples, (i.e.  $M < N$ ), and  $\Phi \in \mathbb{R}^{M \times N}$  is the sensing matrix.

In order to reconstruct the original signal from its compressed samples, the signal  $\mathbf{x}$  must have a sparse representation in a specific domain (i.e.  $\mathbf{x}$  can be represented by few coefficients). The signal  $\mathbf{x}$  can be modeled as  $\mathbf{x} = \Psi \cdot \alpha$ , where  $\Psi \in \mathbb{R}^{N \times P}$  is the dictionary matrix and  $\alpha \in \mathbb{R}^{P \times 1}$  is the coefficient vector. Thus, the acquisition process can be modelled as follows:

$$\mathbf{y} = \Phi \cdot \mathbf{x} = \Phi \cdot \Psi \cdot \alpha \quad (1)$$

If the signal has only  $K$  non-zeroes coefficients, the others  $P - K$  coefficients could be discarded to obtain an estimate of the vector  $\mathbf{x}$ . However, the position of the non-zero elements is not known, so the mathematical problem aims to find  $\hat{\alpha}$ , an estimation of  $\alpha$ , as the maximally sparse solution subject to (1). The dictionary matrix optimization proposed in this paper

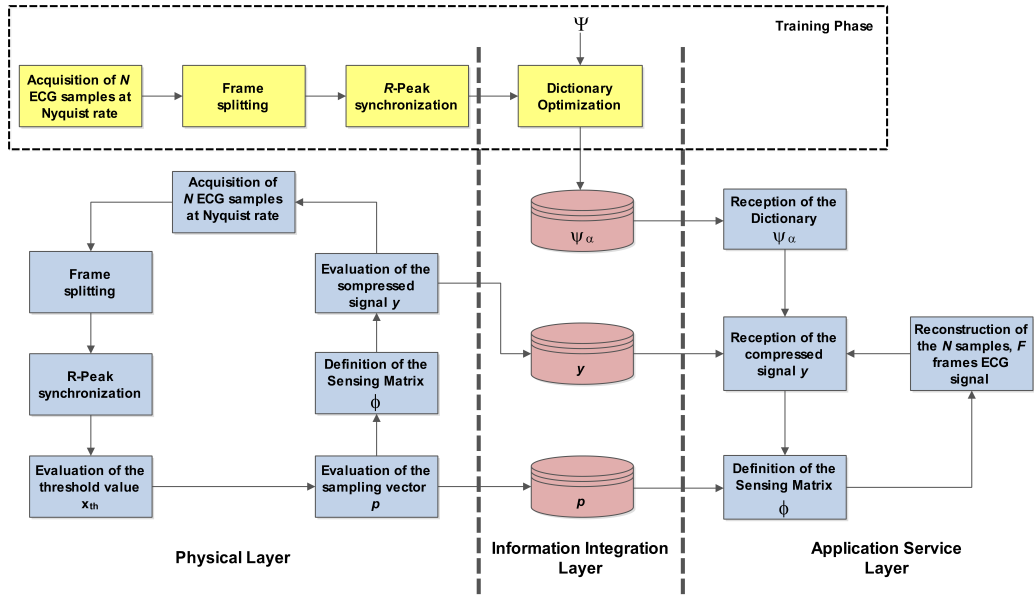


Fig. 1. An overview of the utilization of the proposed dictionary matrix optimization process in continuous real-time ECG monitoring.

is applied to the CS (i.e. compression and reconstruction) algorithm proposed in [21]. For the sake of clarity, in the following, a brief explanation of this algorithm is reported. Usually, in CS applications for ECG signals, the sensing matrix,  $\Phi$ , is randomly constructed, according to several probability density functions. For example, in [13], the authors compared the reconstruction performance of CS methods, which adopt three different distributions for defining the sensing matrix: (i) Gaussian, (ii) Bernoulli, and (iii) sparse (i.e. non-uniform sampling). The main disadvantage of adopting such randomly constructed matrix is that the reconstruction performance may significantly vary, depending on the correlation between the sensing matrix elements and the acquired samples. The method proposed in [21] overcomes this limit by adopting a sensing matrix that is not randomly generated, but depends on the ECG signal to be compressed. The sensing matrix  $\Phi$  is designed with the idea of performing the cross-correlation between the ECG signal,  $\mathbf{x}$  and the pulse train signal (i.e. sampling vector)  $\mathbf{p}$ , which contains ones where the contribution of the signal is higher than a certain threshold  $x_{th}$ , and zero otherwise. The first row of the matrix is the vector  $\mathbf{p}$ , defined as follows:

$$p(k) = \begin{cases} 1, & \text{if } x_a(k) \geq x_{th} \\ 0, & \text{if } x_a(k) \leq x_{th} \end{cases}, \quad (2)$$

where  $x_a$  is defined as:

$$\mathbf{x}_a = |\mathbf{x} - x_{avg}| \quad (3)$$

with  $x_{avg}$  obtained by performing the average of the samples  $\mathbf{x}$ . The threshold value  $x_{th}$  was chosen according to the result reported in [21]. The other rows are shifted versions of the  $\mathbf{p}$  vector, with each row delayed respect to the previous one of an integer quantity equal to the Compression Ratio (CR), defined as the ratio between the number of non compressed samples and the number of the compressed ones. By considering  $M$

rows, the pulse train samples are moved along the entire  $N$  samples of  $\mathbf{x}$ . The dictionary matrix chosen is based on the Mexican hat wavelet (see Section III), and an Orthogonal Matching Pursuit (OMP) [26], [27] algorithm is used in order to find  $\hat{\alpha}$ . Finally the ECG signal can be reconstructed as follows:

$$\hat{\mathbf{x}} = \Psi \cdot \hat{\alpha} \quad (4)$$

### III. THE PROPOSED METHOD

On which regards the IoT integration, the proposed method could be deployed by covering three different layers: (i) *Physical layer*, which consists of the sensor node and it is responsible of ECG acquisition and CS encoding, (ii) *information integration layer*, which consists of a *Server* containing a database for data storage, (iii) *application service layer* consisting of the end-user device that is responsible of data reconstruction from the CS encoded samples. In order to obtain the optimized dictionary that is used in the ECG monitoring, the proposed method presents a preliminary *Training Phase*. Initially, the unoptimized dictionary matrix,  $\Psi$ , is chosen (see Subsection A). The ECG signal is acquired from the sensor, divided into frames, one for each heart beat, and aligned on the R peak. In order to ensure proper training, at least two minutes of the ECG signal has to be acquired. After the acquisition, the signal is transmitted to the database where the OMP for Multiple Measurement Vector (MMV), called M-OMP (Multiple Orthogonal Matching Pursuit) algorithm is used to optimize the dictionary matrix, according to the acquired patient ECG signals. The obtained dictionary  $\Psi_\alpha$ , is stored in the database and transmitted to the *Application Layer*. Furthermore,  $\Psi_\alpha$  represents the new dictionary matrix that will be used in the monitoring of the ECG signals (see Subsection B).

After this preliminary *Training Phase*, the real-time monitoring can start. The ECG signal is acquired from the sensor, aligned and divided into frames of  $N$  samples. For each of these frames,  $x_a$  is calculated using (3), thereafter, the pulse train signal  $\mathbf{p}$  and the sensing matrix  $\Phi \in \{0, 1\}^{M \times N}$  are constructed. Following (1), the compressed vector of  $M$  samples,  $\mathbf{y}$ , is obtained. The sensors transmit  $\mathbf{y}$  and  $\mathbf{p}$  to the database.

The *Application Layer* receives  $\mathbf{y}$  and  $\mathbf{p}$ , and it uses the optimized dictionary matrix  $\Psi_\alpha$  to estimate the coefficients  $\hat{\alpha}$  from the compressed signal  $\mathbf{y}$  via the OMP algorithm. Lastly, the estimate  $\hat{\mathbf{x}}$  is calculated. In Fig. 1, an architectural overview of the utilization of the proposed dictionary matrix optimization process in continuous real-time ECG monitoring is reported. The performance of the proposed method depends on multiple factors, such as: (i) the choice of the  $\Psi$  matrix, (ii) the algorithm used for dictionary optimization, (iii) the algorithm used for signal reconstruction.

### A. Dictionary Matrix Design

As stated in [21] and [25], the best dictionary that achieves the highest reconstruction performance for the ECG signals is defined according to the Mexican hat kernel [28], defined as:

$$\psi(a, b) = \frac{2}{\sqrt{3}a \cdot \pi^{1/4}} \cdot \left[ 1 - \left( \frac{n-b}{a} \right)^2 \right] \cdot \exp^{-\frac{1}{2} \left( \frac{n-b}{a} \right)^2} \quad (5)$$

with  $\mathbf{n} = [0, \dots, N-1]^T$ ,  $a$  is the scaling factor of the Mexican hat kernel and  $b$  is the delay factor. In order to evaluate the effects of those parameters on the reconstruction quality performance of the proposed method, three Mexican hat matrices have been used  $\Psi_1$ ,  $\Psi_2$  and  $\Psi_3$ , which correspond to different scaling and delay factors:

- $\Psi_1$  is the dyadic matrix (see eq.(6)) proposed in [28], where  $a$  follows the power of 2 (i.e.  $a = 2$  for the first  $\frac{N}{2}$  values,  $a = 4$  for the following  $\frac{N}{4}$ , and so on) and  $b$  varies from 0 to  $\frac{N-1}{a}$  with step size of  $a$ .
- $\Psi_2$  is a linear matrix (see (7)), where both  $a$  and  $b$  varies from 0 to  $N-1$ .
- $\Psi_3$  is a matrix (see (8)) where  $a$  follows the geometric progression  $2^n$ ,  $n \in [1, \log_2 N]$  with size step  $\frac{1}{2} <$ , and  $b$  varies from 0 to  $\frac{N-1}{a}$  with step size of  $a$ .

$$\Psi_1 = \begin{bmatrix} \psi(2, 0), \psi(2, 2), \psi(2, 4), \dots, \psi\left(2, 2\left[\frac{N-1}{2}\right]\right), \\ \psi(4, 0), \psi(4, 4), \psi(4, 8), \dots, \psi\left(4, 4\left[\frac{N-1}{4}\right]\right) \\ \dots, \psi(N, 0) \end{bmatrix}. \quad (6)$$

$$\Psi_2 = \begin{bmatrix} \psi(1, 0), \psi(1, 1), \psi(1, 2), \dots, \psi\left(1, \left[N-1\right]\right), \\ \psi(2, 0), \psi(2, 1), \psi(2, 2), \dots, \psi\left(2, \left[N-1\right]\right) \dots, \\ \psi(N, 0) \end{bmatrix}. \quad (7)$$

$$\Psi_3 = \begin{bmatrix} \psi(2, 0), \psi(2, 2), \psi(2, 4), \dots, \psi\left(2, 2\left[\frac{N-1}{2}\right]\right), \\ \psi(2\sqrt{2}, 0), \psi(2\sqrt{2}, 2\sqrt{2}), \psi(2\sqrt{2}, 4\sqrt{2}), \\ \dots, \psi\left(2\sqrt{2}, 2\sqrt{2}\left[\frac{N-1}{2\sqrt{2}}\right]\right) \\ \dots, \psi(N, 0) \end{bmatrix}. \quad (8)$$

Furthermore, in order to allow the reconstruction of the observed signal waveform, the vector  $\mathbf{u} = [1, \dots, 1]^T$  with  $\mathbb{R}^{N \times 1}$  has been added as last column of the  $\Psi$  matrix for all the considered cases, such to take into account possible offset of the signal waveform.

### B. Optimization Method

The dictionary matrix optimization is based on finding, from a chosen dictionary matrix  $\Psi$ , a sub-matrix  $\Psi_\alpha$  formed by a reduced number of column of the  $\Psi$  matrix, that depends on the ECG signal of the patient. To ensure reconstruction of the signal, at least  $K = M$  column of  $\Psi$  must be used. Using the optimized dictionary matrix  $\Psi_\alpha$  makes that, the OMP algorithm used in reconstruction, resolves the minimization problem on a domain with smaller dimension. In order to find the optimized dictionary matrix  $\Psi_\alpha$ , an M-OMP algorithm has been used. The frames acquired during the *Training Phase* form the  $\mathbf{X}$  matrix, and thus the algorithm is applied, performing the following steps [29], [30]:

- 1) The residual  $\mathbf{R}_0 = \mathbf{X}$ , the set of column indices  $\Lambda = \emptyset$  and the counter iteration  $t = 1$  are initialized.
- 2) Find the index  $\lambda_t$  that resolves the equation

$$\lambda_t = \arg \max_{j \in [1, N]} \left( \frac{\|\mathbf{z}_j\|_2}{\|\psi_j\|_2} \right) \quad (9)$$

where  $\mathbf{z}_j = \mathbf{R}_{t-1}^T \psi_j$  and  $\psi_j$  is the  $j$ -th column of  $\Psi$ .

- 3)  $\Lambda$  and  $\Psi$  are updated,  $\Lambda_t = \Lambda_{t-1} \cup \lambda_t$ ,  $\Psi_t = [\Psi_{t-1} \lambda_t]$ .
- 4) The least square approximation is performed and the  $\alpha$  coefficient is evaluated

$$\alpha_t = \arg \min_{\alpha} \|\mathbf{X} - \Psi_t \alpha\|_2. \quad (10)$$

- 5) The new residual is calculated

$$\mathbf{R}_t = \mathbf{X} - \Psi_t \alpha_t. \quad (11)$$

- 6) The iteration counter  $t$  is incremented, and the algorithm checks for the following stop conditions:

- $t$  is greater than the number of ECG samples per frame  $N$ .
- The new residual  $\mathbf{R}_t$  is lower than a fixed threshold  $\mathbf{r}_{th}$ .

if none of those two conditions are met, the algorithm returns to step 2).

Once the above described algorithm is terminated, the  $\Lambda$  set contains the indexes of the columns that have to be chosen in order to create the matrix  $\Psi_\alpha$ . By knowing the dictionary matrix and the sensing matrix, the *Application Service Layer*

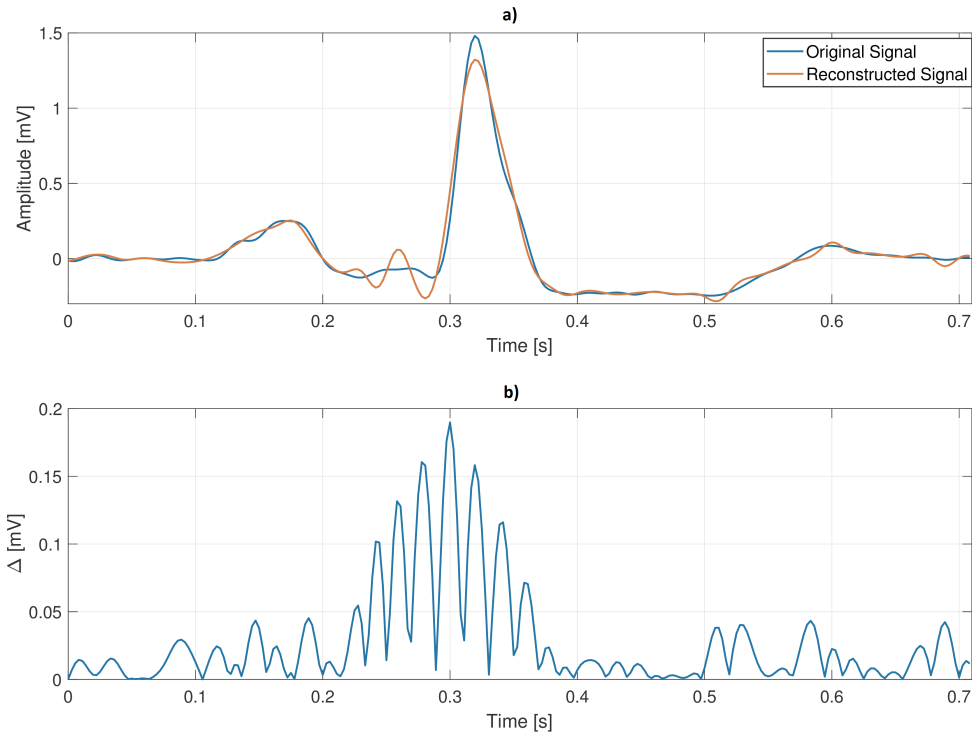


Fig. 2. a) The MIT-BIH arrhythmia database signal *No.105* reconstructed, method reported in [21]  $CR = 8$ . b) Absolute error of the reconstructed signal respect to the original one

runs the OMP algorithm to estimate the coefficients  $\hat{\alpha}$ . Finally, instead of using (4) the signal will be reconstructed as expressed in:

$$\hat{\mathbf{x}} = \Psi_{\alpha} \cdot \hat{\alpha} \quad (12)$$

#### IV. EXPERIMENTAL RESULTS

The method presented in Section III has been implemented in MATLAB and several ECG signals from the PhysioNet MIT-BIH Arrhythmia Database [31] were used to assess its performance in terms of *PRD*:

$$PRD = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{\|\mathbf{x}\|_2} \cdot 100\% \quad (13)$$

where,  $\mathbf{x}$  is the acquired ECG signal,  $\hat{\mathbf{x}}$  is the reconstructed signal, and  $\|\cdot\|_2$  is the  $\ell_2$  norm. In Fig. 2a and Fig. 3a, a frame of the ECG signal *No. 105* and its reconstruction are overlapped, where Fig. 2a refers to the previous compressing method without the dictionary matrix optimization [21], and Fig.3a refers to the proposed method with optimization. Six minutes of the ECG signal have been acquired, half of which have been used for the dictionary matrix optimization, and the others for assessing the reconstruction quality. For this example, a  $CR$  of 8 was chosen and 498 frames of the ECG signal were acquired. Both signals were framed in records of 512 samples. In Fig. 2b and Fig. 3b, the corresponding absolute differences between the reconstructed and the original signals are reported. An average operation has been performed

on the two differences. In case of matrix optimization, the average value of the difference is 0.018 mV, while without optimization, the average value is 0.028 mV.

In order to evaluate the dictionary matrix providing the highest reconstruction quality, a test has been conducted to assess the *PRD* for several  $CR$  values, using as dictionary matrix  $\Psi_{\alpha1}$ ,  $\Psi_{\alpha2}$ ,  $\Psi_{\alpha3}$ , obtained with a *Training Phase* performed on  $\Psi_1$ ,  $\Psi_2$ ,  $\Psi_3$  reported in (6), (7) and (8), respectively.

In Table I, the obtained results are reported. As it can be seen, when the optimization is not performed, the *PRD* values are higher than all the others. For  $CR < 6$  all the dictionary matrices give almost the same performance, with  $\Psi_{\alpha3}$  having the lowest *PRD*. For all others  $CR$ , the best performance is granted by  $\Psi_{\alpha2}$ . For medical application, a *PRD* lower than 9% [23] indicates a good signal recovery. With the proposed method, it is possible to achieve this performance with  $CR$  lower or equal to 10, instead of 6, that was achieved by the

TABLE I  
COMPARISON OF THE *PRD* VALUES OBTAINED WITH THE CS METHOD PROPOSED IN [21] AND THE CS METHOD PROPOSED IN THIS PAPER, FOR THE ECG SIGNAL *No. 105*.

$CR$	Method presented in [21]	$\Psi_{\alpha1}$	$\Psi_{\alpha2}$	$\Psi_{\alpha3}$
2	1.70	1.60	1.51	1.54
4	3.09	2.75	2.24	2.64
6	6.25	4.67	5.29	4.71
8	11.58	6.80	6.24	6.43
10	19.47	9.62	7.79	9.69

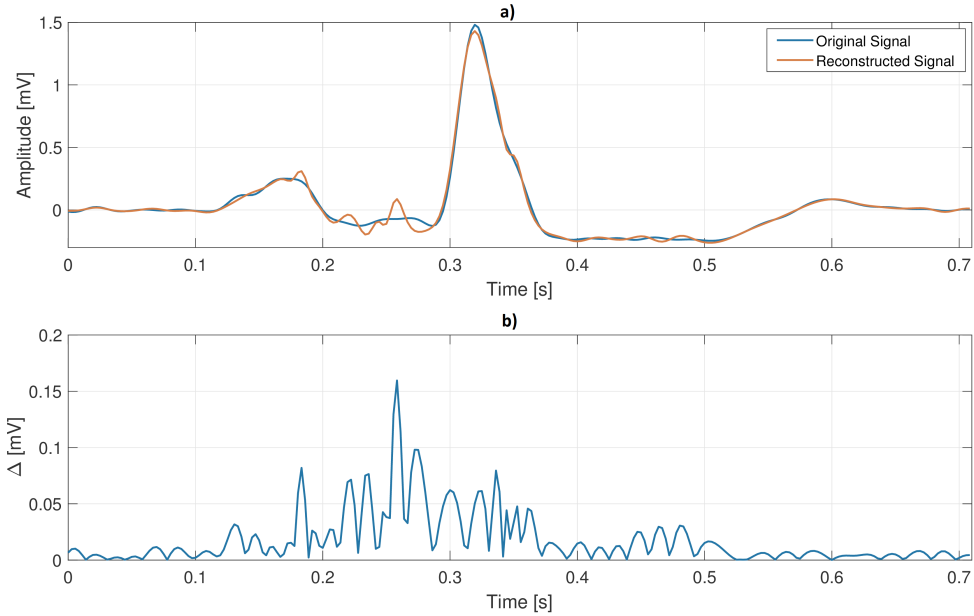


Fig. 3. a) The MIT-BIH arrhythmia database signal *No.*105 reconstructed, proposed method  $CR = 8$ . b) Absolute error of the reconstructed signal respect to the original one

TABLE II  
COMPARISON OF THE PRD VALUES OBTAINED WITH THE CS METHOD PROPOSED IN [21] AND THE CS METHOD PROPOSED IN THIS PAPER, FOR THE ECG SIGNAL *No.* 103.

$CR$	Method presented in [21]	$\Psi_{\alpha 1}$	$\Psi_{\alpha 2}$	$\Psi_{\alpha 3}$
2	1.40	1.39	1.30	1.31
4	3.64	2.77	2.56	2.42
6	11.40	5.22	4.48	4.34
8	25.19	7.46	6.06	6.44
10	41.16	16.78	10.74	14.45

method in [21].

Another test has been performed in order to evaluate the performance of the method when artifacts affect the ECG signal. In this experiment the signal *No.* 103 from PhysioNet MIT-BIH Arrhythmia Database has been used. To evaluate the performance variations caused by artifacts, the test has been performed with the same  $CR$ , number of samples per frame and number of frames used in the previous one.

TABLE III  
COMPARISON OF THE PRD VALUES OBTAINED WITH CS METHOD PROPOSED IN [21] AND THE CS METHOD PROPOSED IN THIS PAPER, FOR THE ECG SIGNAL *No.* 105. WITH TRAINING ON SIGNAL *No.* 103.

$CR$	Method presented in [21]	$\Psi_{\alpha 1}$	$\Psi_{\alpha 2}$	$\Psi_{\alpha 3}$
2	1.70	2.03	1.79	1.88
4	2.15	5.84	5.44	3.83
6	6.25	12.76	6.33	7.53
8	11.58	21.16	9.39	11.65
10	19.47	32.84	14.18	19.97

By comparing the results reported in Table II with those of

Table I, the  $PRD$  values are higher when artifacts are involved. Regardless, the proposed method is capable of achieving  $PRD$  values much lower than the previous method [21] also in this case.

Lastly, in order to evaluate the learning performance of the method, another experiment has been made, where the signal used in the training phase differ from the one used for reconstruction. In the training phase the signal *No.* 103 has been used, while the signal *No.* 105 was adopted in the compression and reconstruction steps. As expected, due to the differences between the two signals the performance of the proposed method decreases. It is worth noting that the two signals were acquired from different patients. Comparing the  $PRD$  values in Table III with Table I and Table II, it is possible to note that the  $PRD$  values increase for all the considered cases. Still, when the  $CR$  is greater than 4, the proposed method shows a better performance then the previous method when using  $\Psi_{\alpha 2}$ , almost achieving a  $PRD$  of 9% instead of 11% with a  $CR = 8$ . In order to evaluate the proposed method, other ECG signals from the MIT-BIH database, in particular number 100, 102 and 103 has been tested. Using signal *No.*100, the proposed method achieves a  $PRD$  value that do not exceed the 9% threshold with a  $CR$  of 8 instead of 4, using signal *No.*102 the threshold value is not exceeded with a  $CR$  value of 6 instead of 4 and, using signal *No.*103, the  $PRD$  remains below 9% with a  $CR$  value of 8 instead of 4.

## V. CONCLUSION AND FUTURE WORK

In this paper, a dictionary matrix optimization method for CS-based sampling of ECG signals has been presented. By using an M-OMP algorithm in an initial training phase, it was

possible to reduce the dimensions of the dictionary matrix  $\Psi$ . Therefore, the OMP algorithm used in reconstruction estimates the coefficients of the signal in a reduced domain, allowing better signal reconstruction quality and reduced execution time of the reconstruction.

Several ECG signals have been used from the PhysioNet MIT-BIH Arrhythmia Database, compressed at various  $CR$  and then reconstructed, to evaluate the  $PRD$  with and without matrix optimization. The results clearly demonstrate that the application of the proposed method allows achieving better performance in terms of  $PRD$  respect to the method proposed in [21].

Future work will be focused on: (i) the energy consumption analysis due to the proposed algorithm, (ii) the implementation on real hardware of the method, and (iii) the improvement of the matrix optimization step by exploiting different pursuit algorithms.

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