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A novel Compressive Sampling method for ECG wearable measurement systems

Francesco Picariello, Grazia Iadarola, Eulalia Balestrieri,
Ioan Tudosa, Luca De Vito¹

*Department of Engineering, University of Sannio,
Piazza Roma, 21, 82100 Benevento, Italy*

Abstract

The paper presents a novel method for the compressed acquisition of electrocardiographic (ECG) signals. The proposed method is intended to be applied to Internet-of-Medical-Things (IoMT) acquisition nodes (i.e. wearable measurement systems) as they can benefit from a reduction of the signal data rate to be transmitted, and the consequent reduction of energy consumption. Being based on Compressive Sampling (CS), the proposed method presents a very low computational complexity on the acquisition node. Moreover, since the sensing matrix is adapted to the acquired signal, it allows achieving a better reconstruction performance compared with the other CS-based methods available in literature.

Keywords: Internet-of-Medical-Things, Wearable Measurement Systems, ECG Signal, Compressive Sampling, Sampling Method

1. Introduction

2 In recent years, wearable measurement systems for measuring physiologi-
3 cal signals and parameters are becoming more complex due to the integration
4 of several sensors and electronic front-ends, allowing to observe and real-time
5 transmit signals, such as electrocardiogram (ECG) and respiration wave. More-
6 over, they are going to be integrated in Internet-of-Things (IoT) systems where

¹Corresponding author e-mail: devito@unisannio.it

7 several acquisition nodes must be connected and managed. In particular, in
8 this field, Internet-of-Medical-Things (IoMT) systems have been proposed to
9 monitor and manage healthcare applications [1, 2].

10 One of the main challenges of IoMT nodes is to meet the energy consumption
11 and size requirements of wearable devices. Moreover, IoMT systems must collect
12 and store data from up to thousands of nodes, resulting in a significant data
13 rate to be handled. A possible compression of this data rate must however
14 guarantee a biosignal integrity, able to comply with medical standards, when
15 it is necessary. Such challenges becomes harder as IoMT nodes are going to
16 include not only Personal Area Network (PAN), but also Wireless Wide Area
17 Network interfaces, such as Wi-Fi, LoRa, Sigfox or Narrowband-IoT (NB-IoT),
18 which are characterized by higher power consumptions and lower data rates.

19 Compression of biosignals has been proposed as a way both to reduce the
20 data rate that the IoMT node has to transmit and to reduce the energy con-
21 sumption of the node [3], since in many cases data transmission is the most
22 expensive activity in terms of energy. In particular, among the different biosig-
23 nals, the compression of the ECG has been faced by many researchers. A first
24 classification of research contributions regarding ECG compression can be made
25 by distinguish hardware and hybrid methods from digital methods. Methods
26 in the former category exploit the sparsity of ECG signal in the time domain
27 to design optimized architectures of analog-to-digital conversion. A method
28 falling in this category is proposed in [4], where the authors designed a level-
29 crossing Analog-to-Digital Converter (ADC) to efficiently sample analog ECG
30 signals. The advantage of solutions in this category is that they provide signal
31 compression without any computational load for the microcontroller of the ac-
32 quisition node. Beside that, they rely on specific hardware designs that must
33 be integrated in the acquisition node. For this last reason, in most cases a com-
34 plete digital solution is preferred. The papers falling in the category of digital
35 methods can be further classified into three types: direct methods, parameter
36 extraction methods and transform domain methods [5]. Direct methods achieve
37 compression by removing the redundancy of the ECG signal in the time domain.

38 A method belonging to this type, described in [6], proposed a protocol for ECG
39 data compression where ECG data are coded as ASCII characters.

40 In [7], the authors proposed a dynamic compression scheme for ultra-low
41 power and real-time wireless ECG applications. It consisted of a digital integrate-
42 and-fire sampler, allowing to represent the ECG signal as a pulse train and a
43 lossless entropy encoder, allowing to encode the timestamps and sign phases of
44 the pulse train to a binary stream. Parameter extraction methods are based
45 on the extraction of some features of the ECG signal such as the P wave (the
46 earliest wave of the ECG cycle, corresponding to the atria depolarization), the
47 T wave (corresponding to the repolarization of the ventricles) or the QRS com-
48 plex (corresponding to the depolarization of the right and left ventricles). A
49 method falling in this category was presented in [8]. This method is composed
50 by a preprocessing phase, where the signal is divided in beats and each beat
51 is further segmented to find the P section, the QRS section and the T section.
52 Each section is filtered with a different filter and the baseline is removed. Then,
53 an encoder searches the best match of the preprocessed beat with the entries of
54 a codebook and performs a Long-Term Prediction (LTP). Finally, the residue
55 between the output of the codebook and the predicted waveform from the LTP
56 is furtherly coded. In transform domain methods, the ECG signal is projected to
57 a transform domain by means of a linear orthogonal transformation. Then the
58 coefficients in the transformed domain are properly encoded. Some widely used
59 transforms include Discrete Fourier Transform (DFT), Discrete Cosine Trans-
60 form (DCT), Walsh Transform and Discrete Wavelet Transform (DWT) [5], [9].
61 In [10], the ECG is compressed by first evaluating the DWT based on the Db6
62 wavelet function. Then, the obtained coefficients are selected by the application
63 of a higher order statistics thresholding. The compressed signal is obtained by
64 linear prediction coding and Huffman coding. The transform domain methods
65 have gained a significant attention due to their capability of accurately repre-
66 sent the ECG signal also at moderate compression ratios. However, most of
67 them are unsuitable for a real-time implementation in acquisition nodes with
68 constrained resources, due to their computational complexity and large buffer

69 memory requirements [11]. Hybrid approaches, combining methods from dif-
70 ferent categories have been proposed in [11] and [12]. The method in [11] first
71 detects the beats, it divides each beat into plain and complex blocks, based on
72 their standard deviation. Then, specific compressions are applied to the two
73 block types. The method in [12] faces the problem of unacceptable distortion
74 of abnormal beats for high compression ratios. It uses a Support-Vector Ma-
75 chine (SVM) binary classifier to identify abnormal beats. Then a wavelet-based
76 compression is used for abnormal beats, while normal beats are compressed in
77 groups by means of a hybrid encoder, employing a combination of wavelet and
78 Principal Component Analysis (PCA).

79 Alternatively, Compressive Sampling (CS) has been proposed for ECG signal
80 compression. The advantage of CS is its capability of achieving performance
81 comparable with transform-domain methods, while moving the computational
82 load from the acquisition node to the receiving node. Since the receiving node
83 is usually located on the Internet cloud, it has much greater computational
84 resources available. Therefore, CS methods allows to realize ECG compression
85 also on sensing nodes with constrained resources. For this reason, CS represents
86 a widely proposed solution for data compression in IoT systems [13], where the
87 acquisition and compression can be implemented in resource-constrained nodes,
88 while the reconstruction is actually carried out (where needed) in the cloud.

89 The literature regarding the application of CS for ECG compression is mostly
90 concentrated on the quality assessment and improvement of the reconstructed
91 signal by investigating the impact on the quality of a specific *sensing matrix*,
92 *dictionary matrix*, or *reconstruction algorithm*. (see Section 2 for further details
93 about CS) [14]. In [15], the authors compared the performance of the ECG
94 reconstruction with the application of different dictionary matrices, based on
95 the Discrete Wavelet Transform, belonging to several wavelet families, such as
96 Coiflet, Daubechies, Symlet, biorthogonal and reverse biorthogonal. Another
97 comparison of several dictionaries was reported in [14], where the dictionary
98 matrix was based on the Daubechies db4, Gabor, and mexican hat and spline
99 wavelets. Regarding the sensing matrix, often Gaussian and Bernoulli random

100 matrices are used as it has been proven their incoherence with Fourier and
101 wavelet dictionaries. In [16], the authors evaluated the Toeplitz, Circulant and
102 Triangular structured sensing matrices, because they do not require the random
103 number generation and therefore are easier to implement and less complex. In
104 [17] and [18], a CS-based sensing scheme using a Deterministic Binary Block
105 Diagonal matrix (DBBD) as sensing matrix is utilized. In particular, in [17] a
106 hardware implementation of the sensing scheme is also proposed and compared
107 with the random demodulator Analog-to-Information Converter architecture.
108 In [18], a digital CS scheme using the same sensing matrix is proposed and
109 compared with Gaussian random matrices. About reconstruction algorithms,
110 Basis Pursuit (BP) and Orthogonal Matching Pursuit (OMP) are mainly used in
111 the literature. In [16], also Compressed Sampling Matching Pursuit (CoSaMP)
112 and Normalized Iterative Hard Thresholding (NIHT) have been evaluated for
113 ECG reconstruction. Alternative approaches have been proposed in [19] and in
114 [20]. In the former, a parametric model of the ECG signal is used and the signal
115 recovery is achieved by means of the Differential Evolution algorithm. In the
116 latter, a time-normalized agnostic dictionary created by the PCA of training
117 signals is instead used as signal base.

118 This paper aims to propose a new digital CS-based ECG compression method
119 where a deterministic sensing matrix, adapted to the acquired signal, is utilized.
120 Differently from random sensing matrices, the sensing matrix does not require
121 the random number generation. Moreover, being adapted to the signal, the
122 sensing matrix contains more information on the signal features and therefore it
123 can guarantee a better reconstruction quality, than other deterministic matrices.

124 The present research aims to realize the ECG signal compression to be inte-
125 grated in the smart wearable device of the Ambient-intelligent Tele-monitoring
126 and Telemetry for Incepting & Catering over hUman Sustainability (ATTI-
127 CUS) project [21]. The project main objective is to develop a telemedicine
128 system where physiological signals are acquired by means of a smart T-shirt
129 and possible anomalies in the parameters are discovered.

130 A preliminary version of the proposed method was presented in [22]. In

131 the work presented here, the aforementioned method was further improved and
 132 assessed. In particular, the compression algorithm was modified such that the
 133 sensing matrix is not evaluated in each frame, but only whether a significant
 134 change in the signal distribution is found. Moreover, the proposed method has
 135 been compared against two state of the art methods performing CS-based ECG
 136 signal acquisition.

137 The rest of the paper is organized as follows. In Section 2, some back-
 138 ground knowledge about CS is given. In Section 3, the proposed CS-based ECG
 139 compression scheme is presented. The experimental evaluation is presented in
 140 Section 4. Finally, Section 5 presents the conclusions and future work.

141 2. Fundamentals of Compressive Sampling

142 CS is based on the assumption that the ECG signal is sparse in a transform
 143 domain, i.e. its representation in such domain is a vector with few elements. In
 144 particular, let us consider a vector \mathbf{x} of N samples acquired in a certain time
 145 window, at Nyquist rate, expressed as:

$$\mathbf{x} = \mathbf{\Psi}\boldsymbol{\theta}, \quad (1)$$

146 where $\mathbf{\Psi}$ is a $N \times N$ matrix describing the domain transformation, often called
 147 *dictionary matrix*, and $\boldsymbol{\theta}$ is the vector of the coefficients in the transformed
 148 domain. The vector $\boldsymbol{\theta}$ is assumed to be K -sparse, i.e. it contains at most K
 149 elements. Under the sparsity assumption, the compression is actually performed
 150 by multiplying the acquired ECG samples by a $M \times N$ *sensing matrix* $\mathbf{\Phi}$, with
 151 $M < N$:

$$\mathbf{y} = \mathbf{\Phi}\mathbf{x}, \quad (2)$$

152 where \mathbf{y} is the M -size vector of the compressed samples. In order to guaran-
 153 tee the reconstruction, it is necessary that the sensing matrix $\mathbf{\Phi}$ presents a low
 154 coherence with the dictionary matrix, where the coherence is defined as [18]:

$$\mu(\Phi, \Psi) = \sqrt{N} \cdot \max_{i,j} \frac{\phi_i^T \psi_j}{\|\phi_i\|_2 \|\psi_j\|_2}, \quad (3)$$

155 where ϕ_i^T and ψ_j are the i -th row of Φ and the j -th column of Ψ , respectively,
 156 and $\|\cdot\|_2$ indicates the ℓ_2 norm. The reconstruction of the ECG waveform is
 157 actually performed by solving the ℓ_1 minimization problem:

$$\hat{\theta} = \arg \min_{\theta} \|\theta\|_1, \quad \text{subject to: } \mathbf{y} = \Phi \Psi \theta, \quad (4)$$

158 where $\|\cdot\|_1$ indicates the ℓ_1 norm.

159 3. The proposed method

160 In this Section, the proposed method is described. In particular, in Subsec-
 161 tion 3.1 the compression procedure occurring in the acquisition node is discussed,
 162 while in Subsection 3.2 the signal reconstruction, executed at the receiving side,
 163 is presented. Furthermore, in Subsection 3.3 the compressed data rate is de-
 164 scribed, and in Subsection 3.4 the computational complexity is analyzed.

165 3.1. Compression

166 As mentioned in Section 1, in digital CS-based methods, the compression
 167 is operated by multiplying the acquired samples by a sensing matrix. In this
 168 paper, the sensing matrix Φ is chosen such that the vector \mathbf{y} performs a sort
 169 of cross-correlation between the vector \mathbf{x} , consisting of a frame of N samples
 170 of the ECG signal acquired at the Nyquist rate, and the pulse train signal \mathbf{p} ,
 171 consisting of ones where the signal \mathbf{x} has a high contribution and zero elsewhere.
 172 In this way, the M samples of \mathbf{y} contain an information that is somehow related
 173 to the auto-correlation coefficients of \mathbf{x} .

174 The proposed method operates on records of N samples acquired at Nyquist
 175 rate. For each record \mathbf{x} , the average of the samples in the record is performed
 176 to obtain the value x_{avg} . Then, the signal magnitude \mathbf{x}_a is evaluated as:

$$\mathbf{x}_a = |\mathbf{x} - x_{avg}|. \quad (5)$$

177 A threshold value x_{th} is computed in each frame, representing a certain
 178 percentile of the waveform amplitude, by means of a sorting-based algorithm
 179 operating on x_a . Then, x_{th} is obtained according to the defined percentile. An
 180 analysis of the method performance versus the considered percentile is reported
 181 in Section 4.2.

182 The Φ matrix is then updated whether a significant change is found in the
 183 x_{th} value. Otherwise, the Φ matrix of the previous frame is used. The change
 184 of x_{th} is considered significant when the distance between the value evaluated
 185 in the current frame and the one obtained in the previous frame is above a
 186 specified limit ε .

187 In the case the Φ matrix must be updated, an N -size binary vector \mathbf{p} is
 188 constructed by quantizing the signal magnitude \mathbf{x}_a , with the resolution of 1 bit,
 189 according to the threshold x_{th} . Therefore, the n -th element $p(n)$ of \mathbf{p} , with
 190 $n = 0, \dots, N - 1$, is evaluated as:

$$p(n) = \begin{cases} 1, & \text{if } x_a(n) \geq x_{th} \\ 0, & \text{if } x_a(n) < x_{th} \end{cases}. \quad (6)$$

191 Once defined the vector \mathbf{p} , the sensing matrix Φ is constructed as follows:

$$\Phi = \begin{bmatrix} p(1) & p(2) & \dots & p(N) \\ p(N - USR + 1) & p(N - USR + 2) & \dots & p(N - USR) \\ \vdots & \vdots & \ddots & \vdots \\ p(USR + 1) & p(USR + 2) & \dots & p(USR) \end{bmatrix} \quad (7)$$

192 where, $USR = N/M$ is the *Under-Sampling Ratio*, expressing a measure of
 193 the data reduction respect to the number of samples acquired according to the
 194 Nyquist criteria. The sensing matrix Φ is built as a circulant matrix obtained
 195 by shifting the pulse train samples of USR positions in each row.

196 The whole compression procedure is summarized by a block scheme as de-
 197 picted in Fig. 1. For the generic n -th frame, the \mathbf{x}_a vector is evaluated as in (5)
 198 and the $x_{th}(n)$ value is obtained, according to the chosen value of percentile.

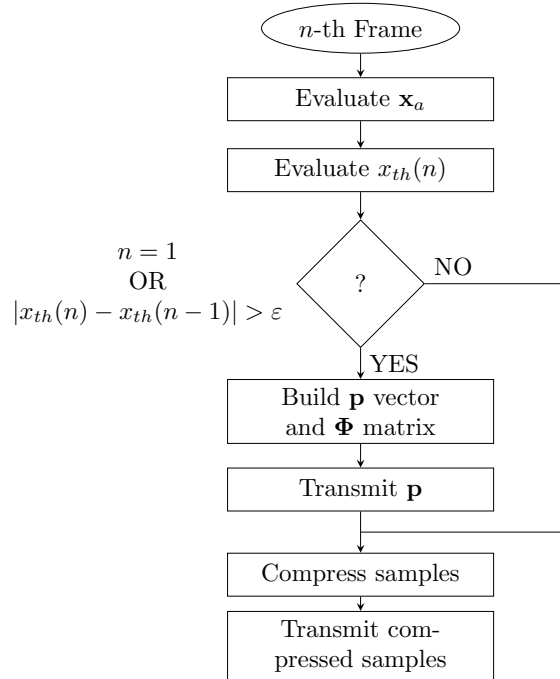


Figure 1: Block diagram of the compression procedure. The Φ matrix is actually evaluated only whether a significant change is found in the value of x_{th} .

199 If the current frame is the first one or the absolute difference of $x_{th}(n)$ and
 200 $x_{th}(n-1)$ is greater than a certain value ε , a new \mathbf{p} vector is evaluated, apply-
 201 ing (6) and a new sensing matrix Φ is generated. In this case, it is also necessary
 202 to transmit the \mathbf{p} vector. If instead $n > 1$ and no significant change occurred in
 203 x_{th} (i.e. $\|x_{th}(n) - x_{th}(n-1)\| < \varepsilon$), the values of \mathbf{p} and Φ of the previous frame
 204 are used. Once defined the sensing matrix to be used, the acquired samples are
 205 compressed by the (2) and the compressed samples are transmitted.

206 3.2. Reconstruction

207 As mentioned in Section 1, the ECG signal waveform is reconstructed by
 208 finding the coefficients in the sparsity domain by solving (4). To this aim, a
 209 key role is played by the dictionary matrix (i.e. Ψ) which defines the sparsity
 210 domain. In other words, the dictionary matrix allows transforming the vector

211 of the acquired samples (see eq. (1)) to a sparse vector, i.e., having a reduced
 212 number of elements.

213 As reported in [14], the dictionary that achieves the highest reconstruction
 214 performance for the ECG signal is obtained by means of the Mexican hat wavelet
 215 kernel. In [23], the Mexican hat wavelet matrix Ψ_{base} is defined as:

$$\Psi_{base} = \begin{bmatrix} \psi(2, 0), \psi(2, 2), \psi(2, 4), \dots, \psi\left(2, 2 \left\lfloor \frac{N-1}{2} \right\rfloor\right), \\ \psi(4, 0), \psi(4, 4), \psi(4, 8), \dots, \psi\left(4, 4 \left\lfloor \frac{N-1}{4} \right\rfloor\right), \\ \dots, \psi(N, 0) \end{bmatrix}, \quad (8)$$

216 where $\psi(a, b)$ is a N -size vector that describes the Mexican hat wavelet function,
 217 defined according to the following expression:

$$\psi(a, b) = \frac{2}{\sqrt{3a} \cdot \pi^{1/4}} \cdot \left[1 - \left(\frac{\mathbf{n} - b}{a} \right)^2 \right] \cdot e^{-\frac{1}{2} \left(\frac{\mathbf{n} - b}{a} \right)^2} \quad (9)$$

218 with $\mathbf{n} = [0, \dots, N-1]^T$, a the scaling factor, $a = 2^m$, $m \in \{1, \dots, \lfloor \log_2(N) \rfloor\}$,
 219 and b the delay factor, which depends on a , i.e. $b \in \{0, a, 2a, \dots, a \lfloor \frac{N-1}{a} \rfloor\}$.
 220 Finally, in order to allow the reconstruction of the observed ECG signal in
 221 presence of a low-frequency baseline wander, the vector $\mathbf{u} = [1/N, \dots, 1/N]^T$ is
 222 added as last column of the matrix Ψ that is finally expressed as:

$$\Psi = [\Psi_{base}, \mathbf{u}]. \quad (10)$$

223 3.3. Compressed data rate

224 Since in the proposed CS method, the sensing matrix is adapted to the signal,
 225 it is necessary to provide, for the reconstruction purpose, a coded version of the
 226 vector \mathbf{p} together with the compressed samples, whenever the sensing matrix is
 227 updated. By assuming that each sample is provided with a resolution of b bits,
 228 the resulting compression ratio is slightly lower than the undersampling ratio:

$$CR = \frac{B_0}{B_c} = \frac{bNN_f}{bMN_f + N_pN} = \frac{USR}{1 + USR \frac{N_p}{N_f}}, \quad (11)$$

229 where B_0 and B_c are the data rates before and after the compression, respec-
 230 tively, N_f is the number of frames and N_p is the number of frames where the
 231 matrix is updated.

232 3.4. Computational complexity

233 The proposed CS method presents a very low computational complexity for
 234 the acquisition node. For each acquired frame, the following operations are
 235 needed:

- 236 • $N \log_2 N$ for the evaluation of the percentile x_{th} , considering that a merge
 237 sorting algorithm is used;
- 238 • one subtraction and two comparisons to check for a significant change in
 239 the x_{th} ;
- 240 • if it is needed to update the Φ matrix, N further comparisons are needed
 241 to build the \mathbf{p} vector;
- 242 • $N_1 - 1$ additions, where N_1 is the number of ones in the \mathbf{p} vector, for each
 243 compressed sample are needed to evaluate the compressed frame.

244 The actual value of N_1 varies in each frame. However, its mean value depends
 245 on the considered percentile for the evaluation of the threshold x_{th} . Indicating
 246 with $p\%$ the value of the percentile:

$$E\{N_1\} = N \cdot P\{x(n) > x_{th}\} = N \left(1 - \frac{p\%}{100}\right), \quad (12)$$

247 where $E\{\cdot\}$ represents the expectation operator, and $P\{\cdot\}$ is the probability of
 248 finding $x(n)$ samples higher than x_{th} . Therefore, for each frame, the following
 249 mean number of operations is needed in the worst case when the Φ matrix is
 250 updated:

$$\begin{aligned}
E\{N_{ops}\} &= N \log_2 N + N + 3 + M (E\{N_1\} - 1) = \\
&= N \left[M \left(1 - \frac{p\%}{100} \right) + \log_2 N + 1 \right] - M + 3.
\end{aligned} \tag{13}$$

251 Considering , as an example, a record of $N = 720$ samples acquired at a sam-
252 pling frequency of 360 Samples/s, $USR = 4$ and $p\% = 60$, according to (13), the
253 number of operations for each record is slightly less than 60 000, corresponding
254 to about 30 000 operations per second. Such computational load can be easily
255 sustained by a 32-bit microcontroller, based on the ARM Cortex M4F core,
256 which provides at least 1.27 DMIPS (Dhrystone Millions of Instructions Per
257 Second)/MHz and a clock frequency greater than 50 MHz.

258 At the receiving side, the ECG signal waveform needs to be reconstructed.
259 At this stage, the computational complexity depends on the chosen reconstruc-
260 tion algorithm. BP has generally a complexity $\mathcal{O}(N^3)$. OMP has instead a
261 much lower computational load. In its implementation based on the matrix
262 inversion lemma, the number of operations is [24]:

$$N_{ops} = \mathcal{O}((N + M)S), \tag{14}$$

263 where, S is the number of iterations of the OMP algorithm which is in any case
264 lower than N .

265 4. Results and discussion

266 In this Section, the performance of the method presented in Section 3 is
267 analyzed through several tests implemented in MATLAB. For testing purposes,
268 the ECG signals from the PhysioNet MIT-BIH Arrhythmia Database (available
269 online [25]) have been considered. The MIT BIH database was chosen among the
270 Internet-available ones as it is the most widely used in the scientific literature.
271 Therefore, the results obtained on the ECG signals of this database can be
272 easily compared among several research papers. This database contains 48
273 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from
274 47 subjects studied by the BIH Arrhythmia Laboratory. The recordings were

275 acquired at a 360 Hz sampling frequency per channel with 11-bit resolution over
 276 a 10 mV range. The signals were segmented in $N = 720$ -size frames, while M
 277 depends on the adopted USR value. Before being processed by the proposed
 278 CS method, in each frame the first three harmonics of the power-line signal, at
 279 $\{60; 120; 180\}$ Hz, respectively have been removed in the frequency domain [26].

280 Preliminary assessment phases were conducted on the method with the fol-
 281 lowing aims: (i) to evaluate the method with different reconstruction algorithms,
 282 (ii) to tune the amplitude percentile used in the method to build the \mathbf{p} vector,
 283 (iii) to verify the influence of the ε threshold, which controls the update of
 284 the sensing matrix. In the above mentioned phases, two data-sets of ten ECG
 285 signals from [25] have been used:

$$S_1 = \{100, 106, 107, 115, 117, 118, 119, 221, 223, 228\} \quad (15)$$

$$S_2 = \{101, 109, 122, 124, 200, 202, 205, 217, 219, 234\} \quad (16)$$

286 The first data-set contains the following main beat labels: atrial premature
 287 beats, premature ventricular contractions, paced beats, isolated QRS-like arti-
 288 facts, and right bundle branch block beats. In the second data-set, the main
 289 beat labels are: left bundle branch block beats, aberrated atrial premature
 290 beats, non-conducted P-waves, and nodal (junctional) premature beats. For
 291 each ECG signal, the Percentage of Root-mean-squared Difference (PRD) has
 292 been evaluated as figure of merit [14, 27, 28, 29]. The PRD is computed as
 293 follows:

$$PRD = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{\|\mathbf{x}\|_2} \times 100\%, \quad (17)$$

294 where \mathbf{x} and $\hat{\mathbf{x}}$ are the original and the reconstructed signal, respectively. Then,
 295 two evaluation phases have been carried out. In the former, the method is
 296 characterized on the above mentioned signal data-sets and compared with the
 297 method proposed in [18] (DBBD sensing matrix and DCT dictionary) and the
 298 method reporting the best result in [14] (Bernoulli sensing matrix and two scales
 299 Mexican hat based dictionary). Those methods were selected as they got the

300 better accuracy of reconstruction within CS-based methods. In this analysis
 301 the following figures of merit were evaluated: *PRD*, *PRD* Normalized (*PRDN*),
 302 Mean Square Error (*MSE*), Root Mean Square Error (*RMSE*), Peak Signal to
 303 Noise Ratio (*PSNR*). The used expression of *PRD* is that reported in (17). The
 304 following expressions of *PRDN*, *MSE*, *RMSE* and *PSNR* have been used [12]:

$$PRDN = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{\|\mathbf{x} - \bar{\mathbf{x}}\|_2} \times 100\%, \quad (18)$$

$$MSE = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{N_s}, \quad (19)$$

$$RMSE = \sqrt{\frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2}{N_s}}, \quad (20)$$

$$PSNR = 10 \log_{10} \frac{\max(\mathbf{x})^2}{MSE}, \quad (21)$$

305 where $\bar{\mathbf{x}}$ is the average of the elements of \mathbf{x} , and N_s is the number of samples
 306 of the entire signal under observation.

307 In the latter phase, the method was tested on several types of abnormal
 308 beats, by evaluating the Weighted Diagnostic Distortion (*WDD*) [30], and the
 309 Wavelet Energy-based Diagnostic Distortion (*WEDD*) [31]. *WEDD* was evalu-
 310 ated according to [31] as a weighted sum of the Wavelet *PRD* (*WPRD*):

$$WEDD = \sum_{l=1}^{L+1} w_l WPRD_l \quad (22)$$

311 where L is the number of wavelet levels. The weights w_l and the *WPRD* are
 312 evaluated as:

$$w_l = \frac{\sum_{k=1}^{K_l} d_l^2(k)}{\sum_{m=1}^{L+1} L+1 \sum_{k=1}^{K_m} K_l d_m^2(k)} \quad (23)$$

$$WPRD_l = \sqrt{\frac{\sum_{k=1}^{K_l} [d_l(k) - \tilde{d}_l(k)]^2}{\sum_{k=1}^{K_l} d_l^2(k)}} \quad (24)$$

313 where, K_l denotes the number of wavelet coefficients at the l -th level, $d_l(k)$ and
 314 $\tilde{d}_l(k)$ are the k -th wavelet coefficients of the original and of the reconstructed
 315 signal, respectively.

316 WDD was evaluated according to [12], by considering the following features:
 317 (i) QRS duration, (ii) P-wave height, (iii) P-wave duration, (iv) R-R interval,
 318 (v) QRS amplitude, (vi) PR interval, (vii) QT interval, and (viii) T-wave height.
 319 The features were evaluated by applying the method proposed in [32] for ECG
 320 delineation. For the evaluation of WDD , the following matrix of weights was
 321 used [12]:

$$\mathbf{\Lambda} = \text{diag}([2 \ 2 \ 2 \ 2 \ 1 \ 1 \ 1 \ 1]). \quad (25)$$

322 Therefore, WDD is evaluated as:

$$WDD = \mathbf{\Delta}\mathbf{\beta}^T \cdot \frac{\mathbf{\Lambda}}{\text{tr}(\mathbf{\Lambda})} \cdot \mathbf{\Delta}\mathbf{\beta} \times 100, \quad (26)$$

323 where, $\mathbf{\Delta}\mathbf{\beta}$ is the vector of the normalized differences $\Delta\beta_i$ of the features eval-
 324 uated on the original and reconstructed signal, respectively [30]:

$$\Delta\beta_i = \frac{|\beta_i - \hat{\beta}_i|}{\max\{\beta_i, \hat{\beta}_i\}}. \quad (27)$$

325 4.1. Influence of the reconstruction algorithm

326 In this test, the performance of the proposed method, by employing either
 327 the OMP or BP algorithms in the signal reconstruction, has been evaluated in
 328 terms of PRD averaged among all the signals of the S_1 data-set. The analysis
 329 has been carried out on the first 5 min of the signal recordings, considering
 330 values of the USR ranging from 2 up to 12 with a step of 2. The obtained
 331 results are shown in Fig. 2. As it was expected, the proposed method exhibits
 332 lower PRD if the BP algorithm is employed instead of OMP. In particular, by
 333 considering a PRD less than 9%, which represents a good signal reconstruction
 334 quality for medical applications [28], the OMP algorithm can be adopted with
 335 a maximum USR of 6, while the BP algorithm allows to increase the USR at

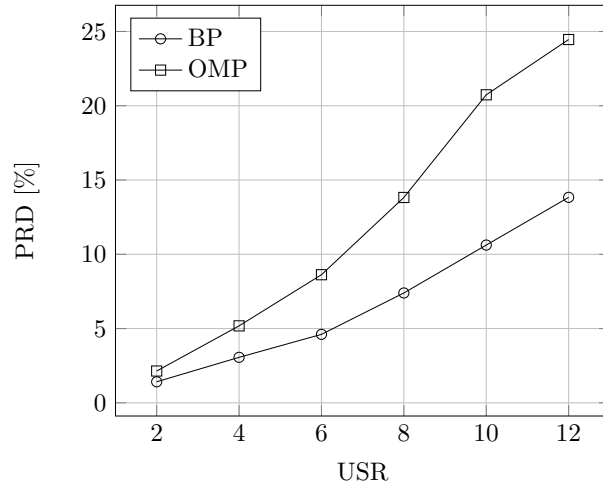


Figure 2: Average PRD over the S_1 data-set using BP and OMP as reconstruction algorithms. BP achieves a better reconstruction quality for all the considered values of USR .

336 a maximum value of 9. However, the BP algorithm exhibits a computational
 337 complexity higher than the OMP. Since it assures a better accuracy in terms of
 338 signal quality reconstruction, BP was used in this paper.

339 4.2. Influence of percentile

340 This analysis aims at evaluating the influence of the percentile used for
 341 the determination of the threshold x_{th} . To this aim, the average PRD over
 342 the first 1 min of the signals contained in the S_1 data-set was evaluated for
 343 different percentiles and USR values. Each signal is reconstructed through the
 344 BP algorithm. The analysis has been carried out according to percentile values
 345 ranging from 20% to 80%, with a step of 10% and for USR values equal to
 346 $\{2, 4, 6, 8, 10\}$. In Fig. 3, the obtained results are depicted. From this figure, it
 347 can be noted that the PRD does not show significant changes with the percentile
 348 in the considered range, for all the USR values. A value of 60% has been chosen
 349 for the further tests.

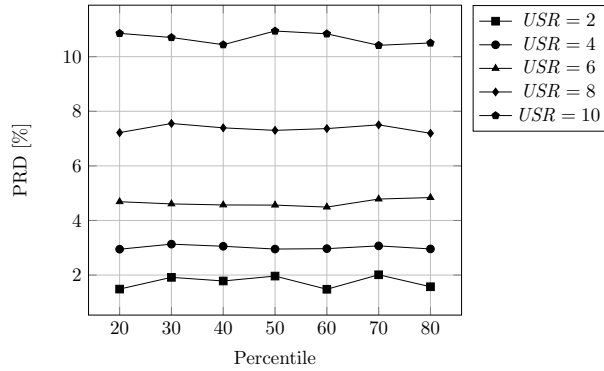


Figure 3: Average PRD of the proposed method versus the percentile and for several values of the USR .

350 4.3. Influence of the ε threshold

351 In Fig. 4, the results in terms of average PRD , evaluated on the first 5 min of
 352 the signals in the S_1 data-set when different values of the USR and ε have been
 353 used, are shown. The PRD is reported versus the CR , which, as mentioned
 354 above, is slightly lower than the USR , due to the need of transmitting the

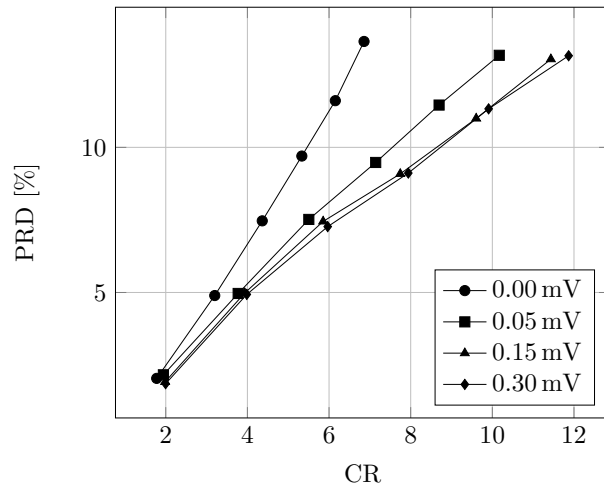


Figure 4: Average PRD , evaluated on the first 5 min of the signals in the S_1 data-set, for different values of USR and three values of the threshold ε : 0.00 mV (sensing matrix changes in all the frames), 0.05 mV, 0.15 mV, and 0.30 mV.

Table 1: Comparison of the results obtained with the proposed method (Proposed) vs. the method proposed in [18] (DBBD+DCT) and the method reporting the best results in [14] (Bernoulli+MexHat2) for the Data-set S_1 : (a) average, (b) standard deviation.

USR	Method	CR	PRD [%]	$PRDN$ [%]	MSE [$\cdot 10^{-5} \text{ mV}^2$]	$RMSE$ [$\cdot 10^{-3} \text{ mV}$]	SNR [dB]	$PSNR$ [dB]
2	Proposed	2.00	1.42	2.30	2.39	4.87	37.72	50.41
	DBBD+DCT	2.00	0.94	1.52	1.58	3.97	41.22	52.16
	Bernoulli+MexHat2	2.00	2.75	4.29	4.75	6.85	31.86	47.47
4	Proposed	3.99	3.06	4.68	5.04	7.04	31.39	47.24
	DBBD+DCT	4.00	3.35	5.00	5.47	7.23	31.21	47.15
	Bernoulli+MexHat2	4.00	4.91	7.49	8.32	9.04	27.09	45.09
6	Proposed	5.97	4.61	7.24	8.16	8.93	27.34	45.22
	DBBD+DCT	6.00	8.21	13.38	14.36	11.79	22.60	42.85
	Bernoulli+MexHat2	6.00	7.59	11.80	13.31	11.40	23.10	43.10
8	Proposed	7.94	7.40	11.71	13.04	11.31	23.18	43.14
	DBBD+DCT	8.00	14.46	23.72	25.10	15.57	17.78	40.43
	Bernoulli+MexHat2	8.00	11.41	17.88	20.05	14.01	19.49	41.29
10	Proposed	9.91	10.62	17.21	18.99	13.66	19.91	41.50
	DBBD+DCT	10.00	19.48	31.88	33.56	18.05	15.18	39.13
	Bernoulli+MexHat2	10.00	16.97	27.14	29.65	17.05	16.07	39.58

(a) Data-set S_1 average.

USR	Method	CR	PRD [%]	$PRDN$ [%]	MSE [$\cdot 10^{-5} \text{ mV}^2$]	$RMSE$ [$\cdot 10^{-3} \text{ mV}$]	SNR [dB]	$PSNR$ [dB]
2	Proposed	2.00	0.60	1.00	0.39	0.40	3.86	6.23
	DBBD+DCT	2.00	0.39	0.57	0.17	0.21	3.53	6.29
	Bernoulli+MexHat2	2.00	1.12	1.04	1.19	0.84	3.57	5.88
4	Proposed	3.99	1.64	1.66	1.28	0.91	4.63	5.81
	DBBD+DCT	4.00	2.15	2.75	2.58	1.65	5.89	5.27
	Bernoulli+MexHat2	4.00	2.36	2.05	2.41	1.30	4.22	5.71
6	Proposed	5.97	1.80	1.84	2.72	1.45	3.51	5.86
	DBBD+DCT	6.00	3.63	6.89	5.49	2.27	4.34	5.71
	Bernoulli+MexHat2	6.00	3.15	3.06	4.60	1.90	3.76	5.79
8	Proposed	7.94	2.73	3.07	3.96	1.64	3.35	5.97
	DBBD+DCT	8.00	7.21	12.44	9.88	3.06	4.37	5.98
	Bernoulli+MexHat2	8.00	4.38	4.75	6.16	2.15	3.64	5.60
10	Proposed	9.91	3.35	5.07	5.66	1.95	2.98	6.11
	DBBD+DCT	10.00	9.73	15.84	12.12	3.30	4.32	6.08
	Bernoulli+MexHat2	10.00	6.39	10.36	8.59	2.52	3.78	5.58

(b) Data-set S_1 standard deviation.

Table 2: Comparison of the results obtained with the proposed method (Proposed) vs. the method proposed in [18] (DBBD+DCT) and the method reporting the best results in [14] (Bernoulli+MexHat2) for the Data-set S_2 : (a) average, (b) standard deviation.

USR	Method	CR	PRD [%]	$PRDN$ [%]	MSE [$\cdot 10^{-5} \text{ mV}^2$]	$RMSE$ [$\cdot 10^{-3} \text{ mV}$]	SNR [dB]	$PSNR$ [dB]
2	Proposed	2.00	1.83	2.47	2.66	5.06	36.10	51.24
	DBBD+DCT	2.00	0.97	1.38	1.45	3.80	40.86	53.62
	Bernoulli+MexHat2	2.00	2.93	4.10	4.46	6.65	31.18	48.78
4	Proposed	3.98	3.33	4.63	4.91	6.96	30.44	48.41
	DBBD+DCT	4.00	3.29	4.47	4.93	6.85	31.02	48.70
	Bernoulli+MexHat2	4.00	5.48	7.58	8.17	8.98	25.99	46.19
6	Proposed	5.96	4.98	7.02	7.53	8.60	26.77	46.58
	DBBD+DCT	6.00	7.41	10.72	11.11	10.39	23.60	44.99
	Bernoulli+MexHat2	6.00	8.21	11.48	12.47	11.08	22.35	44.37
8	Proposed	7.92	7.79	10.94	11.60	10.72	22.89	44.64
	DBBD+DCT	8.00	12.57	18.26	18.46	13.34	19.34	42.86
	Bernoulli+MexHat2	8.00	11.75	16.70	18.04	13.33	19.15	42.77
10	Proposed	9.88	10.63	15.06	16.12	12.64	19.99	43.19
	DBBD+DCT	10.00	17.50	25.57	25.98	15.81	16.44	41.41
	Bernoulli+MexHat2	10.00	16.68	24.14	25.49	15.82	16.22	41.30

(a) Data-set S_2 average.

USR	Method	CR	PRD [%]	$PRDN$ [%]	MSE [$\cdot 10^{-5} \text{ mV}^2$]	$RMSE$ [$\cdot 10^{-3} \text{ mV}$]	SNR [dB]	$PSNR$ [dB]
2	Proposed	2.00	1.22	1.11	1.24	1.03	4.92	2.40
	DBBD+DCT	2.00	0.36	0.40	0.18	0.24	3.41	2.51
	Bernoulli+MexHat2	2.00	1.04	0.80	0.93	0.70	3.29	2.28
4	Proposed	3.98	1.57	1.52	1.31	0.91	4.23	2.40
	DBBD+DCT	4.00	1.80	1.77	2.33	1.63	5.37	2.70
	Bernoulli+MexHat2	4.00	2.31	1.95	2.00	1.11	3.95	2.27
6	Proposed	5.96	2.15	2.19	2.13	1.20	3.79	2.48
	DBBD+DCT	6.00	3.50	5.48	3.74	1.86	4.54	2.82
	Bernoulli+MexHat2	6.00	3.31	2.83	3.34	1.47	3.57	2.27
8	Proposed	7.92	2.98	3.13	2.42	1.14	3.98	2.54
	DBBD+DCT	8.00	6.84	10.75	6.81	2.70	5.26	2.92
	Bernoulli+MexHat2	8.00	4.21	4.79	4.65	1.77	3.39	2.46
10	Proposed	9.88	3.69	3.70	3.02	1.20	3.27	2.38
	DBBD+DCT	10.00	9.40	14.04	9.92	3.33	5.25	3.07
	Bernoulli+MexHat2	10.00	6.63	9.68	6.65	2.29	3.64	2.65

(b) Data-set S_2 standard deviation.

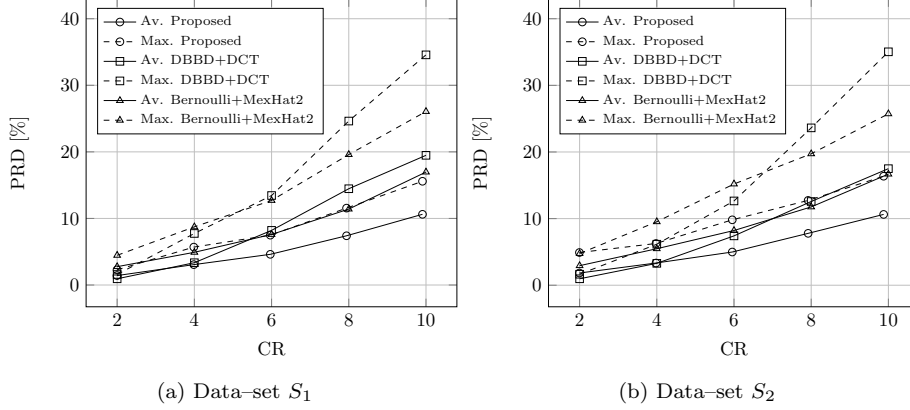


Figure 5: Average PRD (solid line) and Maximum PRD (dashed line) obtained for the S_1 (a) and S_2 (b) for the proposed method (Proposed), the method proposed in [18] (DBBD+DCT), and the method reporting the best performance of [14] (Bernoulli+MexHat2).

355 \mathbf{p} vector, whenever it is updated. In details, the number of times when \mathbf{p} is
 356 updated is controlled by the value ε . Higher ε is, lower is the probability that \mathbf{p}
 357 is updated and CR is closer to USR . It can be observed in Fig. 4 that the PRD
 358 does not change significantly by increasing ε up to 0.30 mV, while a relevant
 359 increase of CR is achieved. For this reason a value of ε of 0.30 mV is selected
 360 for the further tests.

361 4.4. Experimental results

362 The results of the former evaluation phase are shown in Tab. 1 and Tab. 2,
 363 where the values of the considered figures of merit are reported versus the USR
 364 in the case of the proposed method (Proposed), of the method proposed in [18]
 365 (DBBD+DCT) and the method reporting the best results in [14] (Bernoulli+MexHat2).
 366 In particular, Tab. 1 reports the results for Data-set S_1 , while Tab. 2 reports
 367 the results for Data-set S_2 . In each table, the average and standard deviations
 368 of each figure of merit over the signals included in the Data-set are given.

369 The USR is therefore reported in the first column. The second column
 370 reports the method and the third column shows the obtained CR . It can be
 371 seen that the proposed method shows average values of the figures of merit that

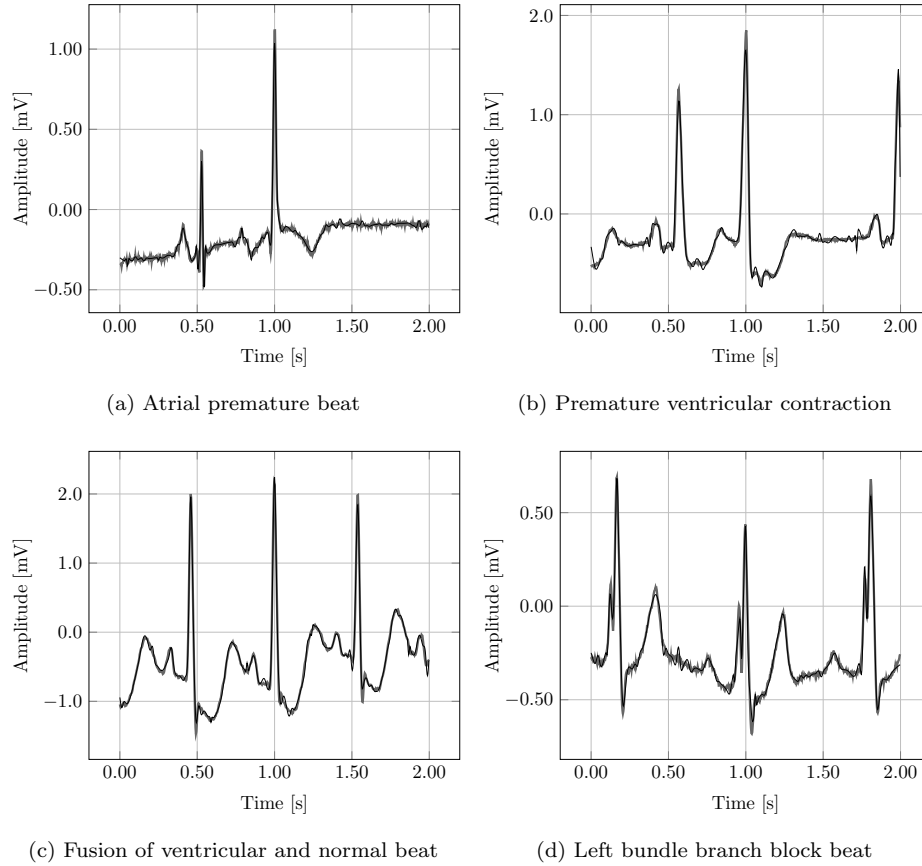


Figure 6: Original waveforms (dashed grey line) and reconstructed waveform (solid black line) of some abnormal beats extracted from the MIT-BIH arrhythmia database signals, after a compression with $USR = 8$: (a) atrial premature beat (Signal no. 222), (b) premature ventricular contraction (Signal no. 105), (d) left bundle branch block (Signal no. 213), and (c) fusion of ventricular and normal beat (Signal no. 111).

Table 3: Results of WDD and $WEDD$ for 4 types of abnormal beats for different values of the USR .

Abnormal beat type	USR	WDD [%]		$WEDD$ [%]	
		Average	Standard deviation	Average	Standard deviation
A (100 beats)	2	0.7	2.1	4.1	3.7
	4	0.9	1.6	5.0	2.2
	6	1.9	3.4	8.2	3.6
	8	3.3	4.1	13.3	7.0
V (41 beats)	2	2.08	4.05	0.96	0.52
	4	3.91	5.22	4.75	3.33
	6	3.16	3.97	7.36	4.35
	8	3.78	5.02	12.72	7.37
F (100 beats)	2	0.09	0.25	0.42	0.23
	4	0.28	0.37	1.79	0.81
	6	0.85	1.15	4.44	1.94
	8	1.82	2.78	8.94	3.67
L (100 beats)	2	0.20	0.60	1.94	1.30
	4	0.20	0.67	2.67	1.27
	6	0.42	0.93	5.63	2.70
	8	1.06	1.22	10.54	4.79

372 are better than the method Bernoulli+MexHat2 for all the considered values of
373 CR . Compared with the method [18], the proposed method shows results that
374 are slightly worse for $USR = 2$. Both the methods then give similar values for
375 $USR = 4$. For $USR > 4$ the proposed method shows a much better accuracy.
376 Looking at the standard deviations, it can be observed that, for both Data-sets
377 S_1 and S_2 , the proposed method shows a lower variability, for almost all the
378 figures of merit, for a CR higher than 2.

379 The superiority of the proposed method can be better observed in Fig. 5,
380 where the trend of the average PRD (solid line) and the maximum PRD (dashed
381 line), evaluated on the signals belonging to the Data-sets S_1 (Fig. 5a) and S_2
382 (Fig. 5b), respectively, are reported versus the CR for the three methods. It
383 can be seen that for $CR > 4$ the proposed method achieves a huge average
384 reduction of PRD compared with both the other methods on both the data-
385 sets. Moreover, it shows also a lower variability than the other methods. The
386 higher accuracy of the proposed method than the other methods is due to the

387 adaptation of the sensing matrix to the acquired signal, realized by evaluating
388 and transmitting the \mathbf{p} vector.

389 The latter evaluation phase was devoted to verify the behavior of the pro-
390 posed method in the case of abnormal beats. To this aim, abnormal beats of 4
391 types were selected in the first 10 min of the signal recordings no. 222 (atrial
392 premature beat - A), no. 105 (premature ventricular contraction - V), no. 213
393 (fusion of ventricular and normal beat - F), and no. 111 (left bundle branch
394 block beat - L).

395 The results are reported in Tab. 3. The table reports in the first column
396 the type of abnormal beat and the number of analyzed beats. In the second
397 column, the *USR* is reported. The other columns report the average values and
398 the standard deviation of the *WDD* and *WEDD* figures of merit, respectively,
399 evaluated on the considered beats. As expected, the values of both *WDD* and
400 *WEDD* increase with the *USR*. However, for all the considered types of beats
401 and values of *USR*, the values of *WDD* and *WEDD* result in the ranges of the
402 highest quality categories reported in [30] and [31]. Slightly higher values were
403 found for A and V beat types, mainly for $USR = 8$. This can be due to a
404 non-perfect coverage of the used Mexican hat dictionary for specific beat types.
405 This will be analyzed in a further work where an automatic optimization of the
406 dictionary is planned, with the application of the method proposed in [33].

407 The good reconstruction quality of abnormal beats can be seen in Fig. 6,
408 where the acquired waveforms (thick grey line) and the reconstructed ones (thin
409 black line), corresponding to 4 frames centered around abnormal beats of dif-
410 ferent types, after the signal has been compressed with $USR = 8$. In particular,
411 atrial premature beat, premature ventricular contraction, fusion of ventricular
412 and normal beat and left bundle branch block beat are reported in Fig. 6a,
413 Fig. 6b, Fig. 6c and Fig. 6d, respectively. It can be seen a good overposition of
414 the thin black line (reconstructed signal) over the thick grey line (original ac-
415 quired signal) that allows preserving all the characteristic features of the wave-
416 form.

417 **5. Conclusion**

418 In this paper, a novel method for the compressive sampling of ECG signals, is
419 presented. The method is based on the idea of building a sensing matrix, which
420 is adapted on the acquired signal frame. In particular, it is a circulant matrix,
421 containing zeros and ones, obtained by quantizing (with the resolution of 1 bit)
422 the magnitude of the acquired signal. The adapted sensing matrix guarantees
423 that the significant portions of the signal waveform are actually contained in
424 the compressed version, thus allowing a more accurate reconstruction respect
425 to the methods already available in scientific literature. The sensing matrix is
426 then used in combination with a modified Mexican hat wavelet dictionary that
427 allows also the reconstruction of the signal wander for each processed frame.

428 The experimental results, obtained on signal recordings from the PhysioNet
429 MIT-BIH Arrhythmia Database, showed that the proposed method achieves a
430 better accuracy in ECG signal reconstruction than the other methods based on
431 compressive sampling. The good ECG signal reconstruction accuracy was also
432 confirmed on abnormal beats of several types.

433 Future work will be focused on a further improvement of the used dictionary,
434 such to better adapt it to the different ECG signal waveforms. Moreover, the
435 implementation and testing of the proposed method on an IoMT system is
436 planned.

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