Multi-class Detection of Arrhythmia Conditions Through the Combination of Compressed Sensing and Machine Learning

Giovanni Rosa[1], Marco Russodivito[1], Gennaro Laudato[1], Angela Rita Colavita[2], Luca De Vito[4], Francesco Picariello[4], Simone Scalabrino[1,3], Ioan Tudosa[4], and Rocco Oliveto[1,3]

[1] STAKE Lab – University of Molise, Pesche (IS), Italy
{giovanni.rosa, marco.russodivito, gennaro.laudato, simone.scalabrino, rocco.oliveto}@unimol.it
[2] ASREM, Campobasso (CB), Italy
angelarita.colavita@asrem.org
[3] Datasound srl, Pesche (IS), Italy
{rocco, simone}@datasound.it
[4] Dept. of Engineering, University of Sannio, Benevento (BN), Italy
{devito, fpicariello, ioan.tudosa}@unisannio.it

Abstract. Medical technologies in the form of wearable devices are an integral part of our daily lives. These devices are devoted to acquire physiological data to provide personal analytics and to assess the physical status of assisted individuals. Nowadays, thanks to the research effort and to the continuously evolving technologies, telemedecine plays a crucial role in healthcare. Electrocardiogram (ECG) is one of the source signal that has been widely involved in telemedicine and therefore the need for a quick and precise screening of ECG pathological conditions has become a priority for the scientific community. Based on the above motivation, we present a study aimed at evaluating the applicability of an highly accurate detector of arrhythmia conditions to be used in combination of a compressed version of the ECG signal. The advantage of using a technique of Compressed Sensing (CS) relies on a faster detection of the approach, due to the lower complexity of the method's workflow. We conducted an experimental study to determine if such a detector, working on compressed ECG signal, can achieve comparable results with the original approach applied to the uncompressed signal. The results demonstrated that with a Compression Ratio equal to 16 it is possible to achieve classification metrics around 99%, therefore showing a high suitability of the approach to be involved in contexts of Compressed ECG.

Keywords: Machine Learning · Compressed Sensing · Automatic Detection · ECG · Arrhytmia

1 Introduction

Wearable technologies are becoming more and more present in our daily lives as devices used for tracking activities, customizing user's daily experiences, and monitoring people's health status [58]. The wearable devices fit into the Internet-of-Things (IoT) paradigm, as things equipped with microchips, sensors and wireless communication capabilities [6]. A particular application is directed to the ones called Wearable Health Devices (WHDs) which uses various sensing technologies to collect measurements for body temperature, motion/posture, heart rate, electrocardiogram (ECG), blood pressure, respiration wave, and many other parameters [15,62]. WHDs populate a subclass of IoT called Internet-of-Medical-Things (IoMT) [36]. The adoption of WHDs allows medical practitioners to increase the efficiency of the diagnosis and reduce its costs [27]. This is possible due to the availability of heterogeneous computing on WHDs and cloud-based data storage for further assessment and long-term monitoring of the health status [1].

Many examples of IoMT systems have been recently proposed [13, 36, 39, 44, 63], such as the *ATTICUS* system [7]. This is a system dedicated to the ambient-assisted living based on the analysis of vital and behavioral data thanks to an innovative remote monitoring system. The signals are acquired through a smart T-shirt [7,14] and then sent to an Ambient Intelligence device. All the devices of ATTICUS are capable of (i) predicting anomalous situations (*e.g.,* atrial fibrillation episodes) and (ii) communicating them to a central Decision Support System (DSS) for the final confirmation.

The high quantity of information generated and transmitted by WHDs (*e.g.,* the ones that acquire real-time multi-lead ECG) raised the necessity of adopting compression techniques to reduce the usage of both memory and bandwidth. Domain Transform Methods (DTM) can ensure the production of compressed ECG signals with low loss in terms of clinical information. Such methods, however, increase the local computational load, which results in increased the power consumption. Since WHDs are powered by relatively small batteries, they suffer from limited autonomy. Using lossy compression methods based on Compressed Sensing (CS) — in particular, digital CS methods — allows to alleviate power consumption problems. Such methods require low computational load on microprocessors during the ECG signal compression step. In this case, the aim of ECG signal compression is to reach maximum efficiency of data reduction without loss of diagnostic information [12]. Previous studies have demonstrated that the adoption of CS algorithms is a solution for WHDs only if the diagnostic information (*e.g.,*, ECG morphology) is neither distorted nor lost [53]. If the original ECG signals show sign of a medical conditions, it is possible to devise detection techniques able to directly detect them on the compressed signals [9]. Examples of conditions that can be detected on compressed signals include ventricular ectopic beat, supraventricular ectopic beat, fusion of a normal and a ventricular ectopic beat [38]. However, to the best of our knowledge, there is no approach able to automatically detect arrhythmia conditions on compressed ECG signals.

Among the many conditions for which WHDs could be beneficial, arrhythmia is probably one of the most spread and dangerous. Arrhythmia is a condition in which the heart beats are irregular, excessively rapid or slow. Atrial and ventricular arrhythmias are the two forms of arrhythmias [52]. Even if some arrhythmias are generally regarded to be innocuous, other arrhythmias, particularly ventricular arrhythmias, are extremely deadly. Indeed, ventricular arrhythmias can lead to abrupt cardiac arrest if they are not treated with extreme care and monitored continuously [16].

In this paper, we introduce NEAPOLIS, a **N**ov**E**l **AP**proach for the aut**O**matic rea**L**-time beat-to-beat detect**I**on of arrhythmia condition**S**. NEAPOLIS aims at detecting Bundle Branch Block (BBB), Premature Ventricular Contractions (PVC) and Atrial Premature Beats (APB), and it was designed with the requirements to provide a real-time and accurate detection of such conditions. Thanks to the developments of this extended work, NEAPOLIS is now capable of working with both uncompressed and compressed ECG signals. The set of features is the same regardless the input signal; indeed, we use a combination of state-of-art features (derived from statistics computed on the RR information and from the morphological description of a heartbeat to describe both an uncompressed and a compressed ECG signal.). As for the former, we evaluated the features directly on the sample of the ECG signal. As for the latter, instead, we integrated in the approach a CS technique based on a Deterministic Binary Block Diagonal (DBBD) matrix as sensing matrix and we calculated the features from the signal in the compressed domain.

This paper is an extension of our HEALTHINF'21 work [56]. The novel contribution we provide in this extension is the following:

1. We introduce an extended version of NEAPOLIS which is able automatically classify not only uncompressed ECG signals (like in our previous work), but also compressed ones; we achieve this goal by re-designing the set of features used in our previous work and adopting a CS technique based on a Deterministic Binary Block Diagonal (DBBD) matrix;
2. We evaluate NEAPOLIS on the Physionet MIT-BIH arrhythmia database, by compressing the original signals with several Compression Ratio (CR) factors.

The rest of the paper is structured as follows: Section 2 first describes the arrhythmia conditions and their incidence on the population and then recall the main steps of the original version of NEAPOLIS; in the second part of the section, a brief description of the state-of-the-art methods for the detection in the compressed domain is offered together with a detailed description of the chosen method as CS algorithm for NEAPOLIS. Section 4.1 reports on the design of the study to experiment NEAPOLIS in the compressed domain and Section 4.2 contains the details on the results achieved by the approach. Finally Section 5 concludes the paper and highlights the future works.

2 Background and related work

2.1 The arrhythmia conditions

A bundle branch block can be defined as an abnormality of the electrical conduction system of the heart [18]. In case the defect is originated in the left or right ventricles the blocks are further classified into Right BBB (RBBB) and Left BBB (LBBB). Scientific research studies have reported that BBB has been observed in 8% to 18% of subjects with acute myocardial infarction. It has also been associated with an increased risk of complete heart block and sudden death [34,48]. Before the involvement of thrombolytic treatment—that limits infarct size, improves ventricular morphology and function, and decreases mortality—several studies had reported on the incidence of RBBB in patients with acute myocardial infarction [45]. The range of incidence rate was found to be between the 3% and 29% [11, 32]. In a recent study, conducted on 1015 patient where 38%of them had ST elevation myocardial infarction (STEMI), RBBB was documented in 8% of patients while LBBB in 4% of patients [19]. Also, both left and right BBB have been associated with increased in-hospital and long-term mortality in patients with acute non-ST elevation myocardial infarction (NSTEMI) [33]. RBBB are present with a incidence rate of 7% for those with NSTEMI. It was also found that RBBB is usually the manifestation of infarctions. These latter are often accompanied by heart failure, complete AV block, arrhythmias, and a high mortality rate [4,47,55]. With regard to the LBBB, the incidence in the general population is low, approximately 0.6% of subjects developing it over 40 years [10, 28]. The incidence rate changes if considering patients with chronic heart failure. Indeed, approximately one third of these patients have left bundle branch block (LBBB) on their 12-lead ECG [5, 59].

Premature ventricular complex (PVC) is characterized by early depolarization originating from ventricles. PVC is an electrocardiogram (ECG) finding that is commonly found in the general population and is associated with structural heart disease and an increased risk of sudden death [2, 43]. In the absence of structural heart disease, frequent PVCs have traditionally been considered a benign phenomenon, only requiring medical attention when symptomatic. This understanding has undergone a substantive evolution over the last decade. So-called benign PVCs are now known to have malignant potential in susceptible patients and can manifest as triggers for ventricular fibrillation (VF) and sudden cardiac death [29]. Scientific research studies have reported that PVCs are present in more than the 6% of middle-aged adults, based on a 2-minute ECG [61].

Ranging from 20% to 25% of ischemic strokes occur due to embolic complications caused by atrial fibrillation [17, 25]. In addition, for patients that have experienced ischemic stroke or transient ischemic attacks, in presence of AF they can be exposed to recurrent strokes [65]. Therefore, it is vital to detect paroxysmal atrial fibrillation after stroke or transient ischemic attack and involve anticoagulation treatment in such patients [26, 66]. This diagnose typically includes a 24 hours continuously monitoring. One of the clues that can lead to a early diagnosis of paroxysmal atrial fibrillation are the occurrence of atrial premature beats (APB). APBs are observed frequently in normal subjects and patients with a variety of diseases. They are manifested as an interruption in the heart rhythm with a premature beat having a narrow QRS complex [60]. Indeed, in 24-hour ECG recordings frequent APB are correlated to an increased incidence of paroxysmal AF in patients with ischemic stroke [64].

2.2 Automatic detection of arrhythmia conditions

In literature there are different set of features for capturing both temporal and morphological carachteristics of ECG signals. Zhao et al. [70] proposed an approach for the extraction of features that allows a reliable heart rhythm recognition. They basically used two techniques for the features generation: wavelet was used to extract the coefficients of the transform and autoregressive modelling (AR) to obtain the temporal structures of ECG waveforms. Then, wavelet and AR coefficients were concatenated together to form the feature vector for the classification. They evaluated a large set of outputs that include also our target conditions, but they chose to experiment the method on a subset of the available recordings from the MIT-BIH Arrhythmia[5], a freely accessible and common database of the scientific literature with annotation at heartbeat level. The results showed that the approach provided good performances of classification reaching an accuracy of 99.68%.

Li et al. [41] proposed a method for ECG classification using entropy on Wavelet packet decomposition (WPD) and Random Forest. The authors also experimented the devised method on the MIT-BIH Arrhythmia database but with a different output because they conducted another kind of experiment, focused on a medical standard, *i.e.,* the EC57:1998 standard [3]. The authors stated that although the coefficients by Discrete Wavelet Transform (DWT) or WPD can reveal the local characteristics of an ECG signal, the number of such coefficients is usually so huge that it is hard to use them as features for classification directly. Therefore, they extracted some high-level features from these coefficients for better classification. In the proposed method, they chose the entropy as high level features extractor from a DWT. The results reported on an obtained overall accuracy approximately equal to 94.61%.

Another very important set of features is the one proposed by Leonarduzzi et al. [40], *i.e.,* a set of features derived from the multifractal analysis. The authors stated that this analysis highly suits the analysis of the Heart Rate Variability (HRV) fluctuations, since it gives a description of the singular behavior of a signal. Therefore, the main features of this work are based on the multifractal wavelet leader estimates of the second cumulant of the scaling exponents and the range of Holder exponents, or singularity spectrum. The results demonstrated how these features can be involved in a tool for a precise detection of myocardial ischemia.

Many works from the scientific literature have involved the Fast Fourier Transform (FFT) in their methods for the classification of ECG segments. For instance, Haque et al. [24] proposed a combination of FFT-based and wavelet features. The main findings achieved by the authors was that the wavelet can provide better indicators—rather than the FFT—of small abnormalities in ECG signals.

There are various approach for automatic arrhythmia conditions based on machine learning techniques, as described by [20]. In Table 1 we report some of the most recent and best performing approaches in literature based on different machine learning techniques, including also neural networks and transfer learning. For example, Yildirim et al. [68] presented a new deep learning model for ECG classification using network-based wavelet sequences, called DBLSTM-WS. Their approach was evaluated on the detection of five different heartbeat types, including Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB), with an accuracy score of 99.39%. Yildirim et al. [69] proposed an approach where they combine a convolutional auto-encoder (CAE), to reduce the signal size of arrhythmic beats, with a LSTM classifier. As a result, ECG signals were compressed by an average 0.70% percentage root mean square difference (PRD) rate, with an accuracy score over 99.11% was observed. Moreover, Li et al. [42] proposed a deep learning-based method of cardiac arrhythmia episodes using deep residual networks (ResNet). Their approach was evaluated with both single and 2-lead ECG signals. The resulting classification accuracy is 99.06% for single lead

[5] https://archive.physionet.org/physiobank/database/mitdb/

ECG and 99.38% for 2-lead ECG. Zheng et al. [71] proposed an automatic approach that takes as input ECG signal images, from where using a combined deep learning model composed of CNN-LSTM, can classify 8 different heartbeat types from MIT-BIH database. Their approach achieved an overall accuracy score of 99.01%. Sahoo et al. [57] proposed an automatic approach using an QRS complex features combined with the multiresolution wavelet transform to calssify four types of heartbeats. The overall accuracy achieved is 98.39% using SVM. Osowski et al. [49] proposed a recognition system based on SVM for heartbeat classification. Using Higher Order Statistics (HOS) combined with Hermite, their approach achieves an overall accuracy of 98.18%.

There are also approaches that exploit the advantages of Transfer Learning, with an embedded feature extraction using ECG signal images. For example, Isin et al. [30] proposed AlexNet, a transferred deep convolutional network that can classify up to three different cardiac conditions with a recognition rate of 98.51%. Also, Pal et al. [50] proposed CardioNet that can classify 29 types of arrhythmia conditions from MIT-BIH database with a total accuracy score of 98.92%.

Pandey et al. [52] proposed a relevant work on automatic detection of Arrhythmia conditions. Their approach provides a complete automatic detection of five heartbeat types, including the LBBB, RBBB and PVC. The approach is based on a single Long Short-Term Memory (LSTM) Neural Network as model. The inputs to the model were based on higher-order statistics, wavelets, morphological descriptors, and R–R intervals. Thus, 45 features were in charge of describing the electrocardiogram signals. In details, to extract the features, the authors designed a temporal window of 180 samples sized (half of a second on the MIT-BIH Arrhythmia). The window was centered on each R peak, previously obtained thanks to the annotations of each R wave position available from this database. The features have been evaluated only inside this interval. A 2-fold cross validation was used to evaluate the accuracy of the classification: The entire MIT-BIH arrhythmia database was divided in two folds, *i.e.,* two sub-dataset. Their LSTM model was trained on 40 % (80 % of 50 %) sub-dataset, and 10 % (20 % of 50 %) sub-dataset was dedicated to a preliminary validation phase. The remaining 50 % of the data set was used for testing. After the performance evaluation, the model obtained an overall accuracy equal to 99.37%.

The main difference between NEAPOLIS and the described approaches is that we allow a real-time classification, also achieving a fast and lightweight performing classification. This was mainly due to the features vector of NEAPOLIS that was basically composed of near real-time features and a low-complexity model for the classification. Indeed, Neural Networks are usually more expensive in terms of resources compared to classical machine learning algorithms, also some the described studies does not follow the AAMI standard for the validation of their approach (as the case of the work proposed by Li *et al.* [41]). In the context of this study, we also evaluate the effectiveness of those features in the context of compressed ECG signals.

2.3 Detection in the compressed domain

In this section, a brief description of the state of the art of works evaluating the accuracy of heart disease detectors in the compressed domain is presented.

Study	Heartbeat classes	Features	Technique	Overall Accuracy
Yildirim et al. [68]	5	End-to-end, DWT	DBLSTM-WS	99.39%
Yildirim et al. [69]	5	Encoded features	CAE-LSTM	99.11%
Li et al. [42]	5	End-to-end	ResNet	99.06%
Zheng et al. [71]	8	End-to-end	CNN-LSTM	99.01%
Sahoo et al. [57]	4	QRS, DWT	SVM	98.39%
Osowski et al. [49]	13	HOS, Hermite	SVM	98.18%
Li et al. [41]	5	WPE, RR	RF	94.61%
Isin et al. [30]	3	AlexNet	CNN	98.51%
Pal et al. [50]	29	DenseNet	CardioNet	98.92%
Pandey et al. [52]	5	Temporal, Morphological	LSTM	99.37%

Table 1: Summary of the approaches for the automatic detection of arrhythmia conditions proposed in literature.

The utilization of CS in WHD based monitoring may provide a solution for detection of atrial fibrillation from compressed ECG signals. This detection approach may reduce the time required for digital signal processing algorithms applied on raw (or reconstructed after compression) ECG signals. For example, the problem that persists in existing methods utilized for the detection of atrial fibrillation pathology from compressed ECGs is related to the unsatisfactory classification performance of the used algorithms, especially in where high CR is required [9]. In literature, investigations regarding the applied detection algorithms from compressed ECGs are reported and in the following, a brief review is presented.

The authors of the work proposed in [9] implemented a deep learning method which is able to detect the atrial fibrillation directly from compressed samples of ECG signals without performing the reconstruction step. This method makes use of the measurement matrix (i.e., the sensing matrix) utilized during ECG signal compression to initialize the first layer of a deep neural network in order to obtain a prior information which leads thereafter to obtain an improved classification performance of the desired pathological (e.g., the presence of atrial fibrillation) issue on the investigated ECG signal. Furthermore, the reported experimental results in [9] describe an accuracy of 97.52% and an F1 score of 98.02% for a CR = 10%, and on the other side, the method was assessed against of a CR = 90% reporting a reduction of the accuracy to 6.77% and F1 to 5.31%, respectively.

The work proposed in [37] dealt with an approach that retrieves vital information from a digital compressed single-lead electrocardiogram (ECG) signal by combining Machine Learning and Compressed Sensing. This study was focused on the identification of R-peak occurrences from compressed ECG. The results demonstrated that the use of CS in combination with a ML technique achieve results comparable to the ones applied to the uncompressed ECG signal.

In the work proposed in [38], a heartbeat morphology classifier was presented. This method worked on compressed ECG signals and signal compression was realized through 1-bit quantization. The authors then experimented several machine learning techniques to classify the heartbeats from compressed ECG signals. The obtained results showed that the tool exhibited comparable results with other similar methods that performed the same detection but on uncompressed ECG signals.

2.4 The Compressed Sensing Algorithm

The CS algorithm here adopted is based on a Deterministic Binary Block Diagonal (DBBD) matrix as sensing matrix. In particular, in case of ECG, the DBBD in combination with the Discrete Cosine Transform (DCT) dictionary matrix has been demonstrated to outperform the others CS techniques based on sensing matrix randomly built [54]. Another CS technique for ECG is proposed in [53]. In this case, the sensing matrix is chosen such that the vector of compressed samples is obtained from a sort of cross-correlation between the ECG signal and a vector consisting of ones where the ECG signal has a high contribution and zero elsewhere. Even if the approach of [53] outperforms the DBBD-based method in terms of reconstruction quality, it requires more steps for its implementation, i.e. the determination of the vector containing ones and zero according to a threshold defined from a percentile of the ECG amplitude distribution and also the transmission of this vector to the host. For this reason, in this paper, the DBBD technique has been adopted being more easy for its implementation on low-power device with low computational capabilities.
In general, the CS can be modelled as multiplication between the column vector $\mathbf{x}$ of N acquired samples at Nyquist rate and a $M \times N$ sensing matrix Φ:

$$\hat{\mathbf{y}} = \Phi \cdot \mathbf{x} \tag{1}$$

The $\mathbf{y}$ vector will contain the M compressed samples.
In the case of DBBD, the sensing matrix Φ is defined as:

$$\hat{\Phi} = \begin{bmatrix} \mathbf{1}_{CR} & \mathbf{0}_{CR} & \dots & \mathbf{0}_{CR} \\ \mathbf{0}_{CR} & \mathbf{1}_{CR} & \dots & \mathbf{0}_{CR} \\ \vdots & \dots & \ddots & \vdots \\ \mathbf{0}_{CR} & \dots & \mathbf{0}_{CR} & \mathbf{1}_{CR} \end{bmatrix} \tag{2}$$

where, $CR = N/M$ is the compression ratio, $\mathbf{1}_{CR}$ and $\mathbf{0}_{CR}$ are row vectors of CR ones and zeros, respectively. According to (2), the CR must be an integer, otherwise, the sensing matrix *Phi* cannot be built.

Usually, in the literature, the reconstruction phase is performed with the aim of estimating $\mathbf{x}$ from the compressed vector $\mathbf{y}$, according to the sensing matrix Φ, and a dictionary matrix Ψ. In particular, Ψ is selected according to a specific domain where the signal can be represented by few K non zero coefficients. The first reconstruction step consists in estimating these coefficients (i.e. $\hat{\theta}$) by solving:

$$\hat{\theta} = \arg\min_{\theta} \|\theta\|_1, \quad \text{subject to:} \quad \mathbf{y} = \Phi\Psi\theta, \tag{3}$$

From $\hat{\theta}$, the reconstructed signal $\hat{\mathbf{x}}$ is obtained as follows:

$$\hat{\mathbf{x}} = \Psi \cdot \hat{\theta} \tag{4}$$

As demonstrated in [54], in the case of DBBD compression for ECG signals, the best choice for the dictionary matrix definition is the DCT matrix.
The solving of (3) is usually performed with the Orthogonal Matching Pursuit (OMP) algorithm, which exhibits a computational complexity $O((N+M)S)$, where $S<N$ is the number of iterations. This step exhibits a high computational load that increases with N. Thus, the reconstruction step limits the use of CS in case of real-time systems or early warning implementations. For this reason, the idea underlying this paper is to detect anomalies on ECG signals directly in the compressed domain (i.e. by considering the vector $\mathbf{y}$ of compressed samples), removing the need of reconstruction.

3 Automatically Detecting Arrhythmia Conditions

In this section, we describe NEAPOLIS, an online detector of arrhythmia conditions based on the analysis of heartbeats signals that works both on uncompressed and compressed ECG signals. Figure 1 describes the workflow of NEAPOLIS.

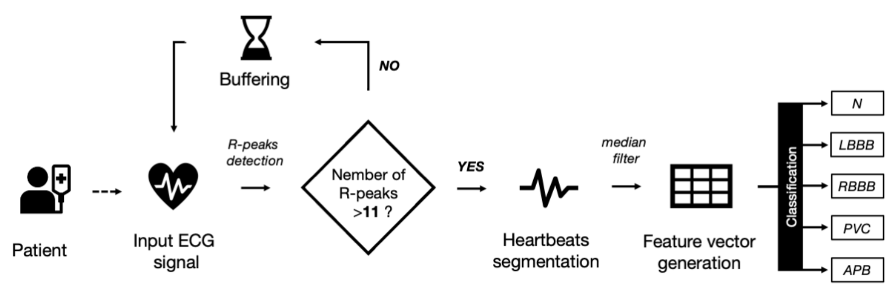

Fig. 1: The workflow of NEAPOLIS for online beat classification.

First, NEAPOLIS receives as input a single lead digital ECG signal. A small portion of the signal is buffered until there are at least 11 R-peaks (*i.e.,* heartbeats). Follows a beat-to-beat segmentation and a 2-step median filter to get rid of baseline drifts. Next, the feature vector is generated and given to a machine learning model to perform the classification. As a result, NEAPOLIS provides a label for the most probable classification among *N* (Normal Sinus Rhythm), *RBBB* (Right Bundle Branch Block), *LBBB* (Left Bundle Branch Block), *PVC* (Premature Ventricular Contraction), and *APB* (Atrial Premature Beat). In the following sub-sections, we describe in detail each component of NEAPOLIS.

3.1 ECG Digital Processing

The digital signal processing embedded in NEAPOLIS is based on the one proposed by [52]. It can be conceptually divided in beat-to-beat segmentation and signal filtering. Both these procedures are triggered only when a long enough portion of a digital single lead ECG is buffered (*i.e.,* at least 11 R peaks). Once these two steps are completed, the features can be extracted from the obtained signal.

First, for the beat-to-beat segmentation, NEAPOLIS evaluates the position of the R peaks from all the buffered ECG segment using a QRS detector, such as the widely used algorithm proposed by [51]. As a result, the R peak positions in the buffered ECG are obtained, then the segmentation process can start. Evaluating a time window of 180 samples, centered on a R peak, all the the samples included in the window are selected. This leads to the definition of a single heartbeat signal, *i.e.,* a sample vector of length 180 centered on a R peak.

After, NEAPOLIS performs the baseline removal on the heartbeat signal. This means that two median filters are applied, where the first is a filter of 200 ms, applied on the raw signal, and the latter is a median filter of 600ms applied on the signal resulting from the application of the first filter. At the end, a set of filtered heartbeat signals are obtained.

3.2 Heartbeat Features

Next subsections describe in detail the features extracted by NEAPOLIS.

After the previous steps, follows the feature extraction phase. In NEAPOLIS we use a set of state-of-the-art features from the literature combined with morphological features. We select only the features that allow a real-time detection on the input signals, with the price of a limited buffered portion of the ECG signal to be processed. Next, we describe in detail the feature used in NEAPOLIS.

- *Energy of Maximal Overlap Discrete Wavelet Transform* The wavelet transform (WT) is a mathematical operator that can be used for the decomposition of time series signals into distinct subsignals. One of the two forms of WT is the DWT. The maximum overlap discrete wavelet transform (MODWT) is a modified DWT. In the MODWT, there is no process of subsampling, therefore leading to a higher level of information in the resulting wavelet and scaling coefficients, when compared to the DWT [22]. For our purposes, we evaluated the MODWT and then extracted the energy features according to the following steps: (i) selection of a mother wavelet function W and the decomposition level L; (ii) decomposition of the original heartbeat signals according to the specified W and L; and (iii) calculation of the energy of each coefficient in each node in the last level L. This procedure has also been partially considered in the feature extractor proposed by [41]. In our case, we used the *db2* Daubechies wavelet function and three levels of decomposition.
- *Autoregressive Model (AR)* As suggested in the method proposed by [70], we involved the calculation of the Autoregressive model (AR) coefficients of order 4. As outcomes, we evaluated the AR coefficients and the reflection coefficients, using the Yule-Walker estimator [21].
- *Multifractal Wavelet Leader* The goal of multifractal analysis is to study signals that present a point-wise Holder regularity variable, *i.e.,* that may largely vary from point to point. When dealing with a signal, performing the multifractal analysis refers to the estimation of its spectrum of singularities. Therefore, the determination of the spectrum of singularities of a signal is important to analyze its singularities [40]. In case of a real-life signal, it cannot be numerically evaluated due

to constraint like finite resolution and the sampling of signals [35]. To overtake this limitation, a multifractal formalism was introduced: the wavelet leaders [31]. In NEAPOLIS, we involved the multifractal wavelet leader estimates of the log-cumulants of the scaling exponents.

– *Fast Fourier Transform* Our approach embeds the evaluation of the Fast Fourier Transform on the heartbeat signal. Indeed, FFT represents a method for extracting helpful information out of statistical features of ECG signal.
– *R-R interval descriptors* These features have been selected from a larger set of R-R statistical descriptor proposed by Pandey et al. [52]. In detail, we selected only the features that can be computed with a limited buffering of the ECG signal. Thus, we excluded from our set o f features the *global-RR interval*, because it represented the average of all the pre-RR values present in the last 20 min. This would not allow NEAPOLIS to perform a real-time detection, even using ECG buffering. As a result, we select the following features:
  - *pre-RR interval*, that is the distance between the actual and previous heartbeat;
  - *post-RR interval*, that is the distance between the actual and next heartbeat;
  - *local-RR interval*, that is the average of 10 previous pre-RR values.

  Within this new study, we opted for removing the information related to the continuity of the R peaks. This choice was due to the considerations (i) that the R peaks are clinical features retrievable with a highly accurate QRS detector, which could impact on the low-complexity of the algorithm designed for this study and (ii) that the R peaks could not be always observed in a compressed domain.
– *Discrete Cosine Transform-based features* Previous work showed that Discrete Cosine Transform (DCT) is the best choice for the reconstruction of the ECG signal from the compressed samples [54]. Therefore, we include features derived from the DCT when NEAPOLIS runs on compressed ECG signals. We used the same order we used for the FFT-based features.

3.3 Beat Classification

The last phase of NEAPOLIS is the beat classification. Once the previously described features are extracted, a normalization step and also data sampling (*i.e.,* SMOTE [8]) are applied. The first transforms the features in a predefined range of values, the latter helps to deal with unbalanced data.

Next, a machine learning model classifies the heartbeats as *N*, *RBBB*, *LBBB*, *PVC*, and *APB*. The only constraint that NEAPOLIS have for that phase is to use a supervised machine learning technique, thus different algorithms can be used. The best configuration of NEAPOLIS, as evaluated in the previous study, is represented by a machine learning pipeline composed of SMOTE sampling, min-max scaler and Random Forest algorithm.

4 The Study

In this section, a detailed description of the study is offered, concerning the study design, the context of the study and the final results.

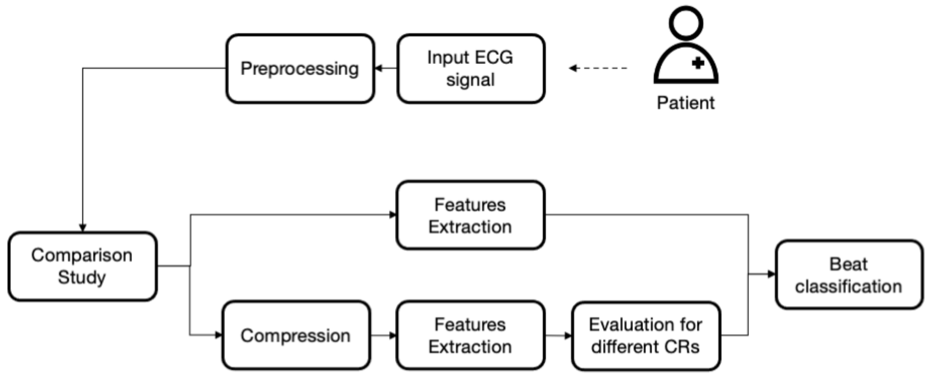

Fig. 2: The experimental workflow designed for this study.

4.1 Study Design

In this section we present the study designed to evaluate the applicability of our approach in the compressed domain. Specifically, when we first presented NEAPOLIS, we observed high classification performances in the classification of the heartbeat in N (Normal Sinus Rhythm), RBBB (Right Bundle Branch Block), LBBB (Left Bundle Branch Block), PVC (Premature Ventricular Contraction), and APB (Atrial Premature Beat). An important role were played by the features vector and therefore by the algorithms chosen to generate it.

In this work, the objective is to evaluate the applicability of such a set of features on a compressed version of the heartbeat signal, in order to assess the applicability of NEAPOLIS also in contexts of compressed data transmissions.

Thus, our new study is steered by the following research questions:

RQ1: *What are the classification performances of* NEAPOLIS *when dealing with* ***uncompressed*** *ECG signals?*
RQ2: *What are the classification performances of* NEAPOLIS *when dealing with* ***compressed*** *ECG signals?*

With the first research question, we aim at evaluating the refined version of NEAPOLIS on the uncompressed signal with respect to the previous version of the approach [56].

With the second research question, we want to verify if NEAPOLIS—applied to compressed data—can reach a classification accuracy comparable to the versions of the approach that work on the uncompressed signal.

Experimental Workflow The workflow of the experimented designed within this work is depicted in Figure 2.

NEAPOLIS was designed to work in the time domain and the main processing steps were basically:

1. the buffering of an ECG single lead trace, according to a minimum amount evaluated on the number of R peaks;
2. the preprocessing aimed at segmenting the trace in heartbeats according to the R peaks and filtering the ECG from noise and artefacts;
3. the features extraction steps where the final features vector was generated to be used as input in the final classification stage.

The extension of NEAPOLIS is resulted in a comparison study between the classification performances of the model in the uncompressed and compressed domain. Therefore—in this study—the compression algorithm is applied right before the evaluation of the final features vector. In this way, it was possible to compare the usefulness of the different features both in the uncompressed than in the compressed domain.

Context of the study The Physionet MIT-BIH arrhythmia database [23, 46] was involved in this study. It is a database widely used in the state of the art for the detection of arrhythmia conditions [46]. This DB contains 48 ambulatory ECG recordings, acquired at 360 Hz sampling frequency and with 11-bit resolution. Cardiologists from Physionet worked to provide annotations for each heartbeat of this DB. The final number of hearbeats labeled are around 110,000 divided into 15 different categories. A standard procedure from the scientific literature [67] can be applied to this DB in order to: (i) remove record with paced beats and (ii) consider only 5 categories of beat annotations: N, LBBB, RBBB, APB and PVC. The distribution of such categories of hearbeats is depicted in Figure 3.

The validation scheme involved in this work is the same used for the initial validation of NEAPOLIS. The scheme refers to a standard procedure [52] that needs an initial decomposition of the dataset into two sub datasets, namely *DS1* and *DS2*. According to the standard procedure, the first one is used as training set while the second as test set.

To guarantee the consistence of the experiment, we have repeated x1000 the splitting process into *DS1* and *DS2*. This helped in avoiding any convenient split on a single run. The validation protocol was therefor applied x1000 and the results were avareged accordingly.

Uncompressed vs Compressed Domain For uncompressed domain it is meant the original version of NEAPOLIS, where the features were evaluated directly on the uncompressed version of the heartbeat while for compressed domain it is meant the domain where the heartbeat is not considered in its entire length but in a compressed version. Indeed, we evaluated the applicability of the compression in NEAPOLIS for different compression ratios.

Specifically, the experiment was designed to compare the classification performances in the compressed domain for the compression ratios in the set 2, 4, 8, 16. This choice was due to:

- the length of the original heartbeat,
- the compression algorithm.

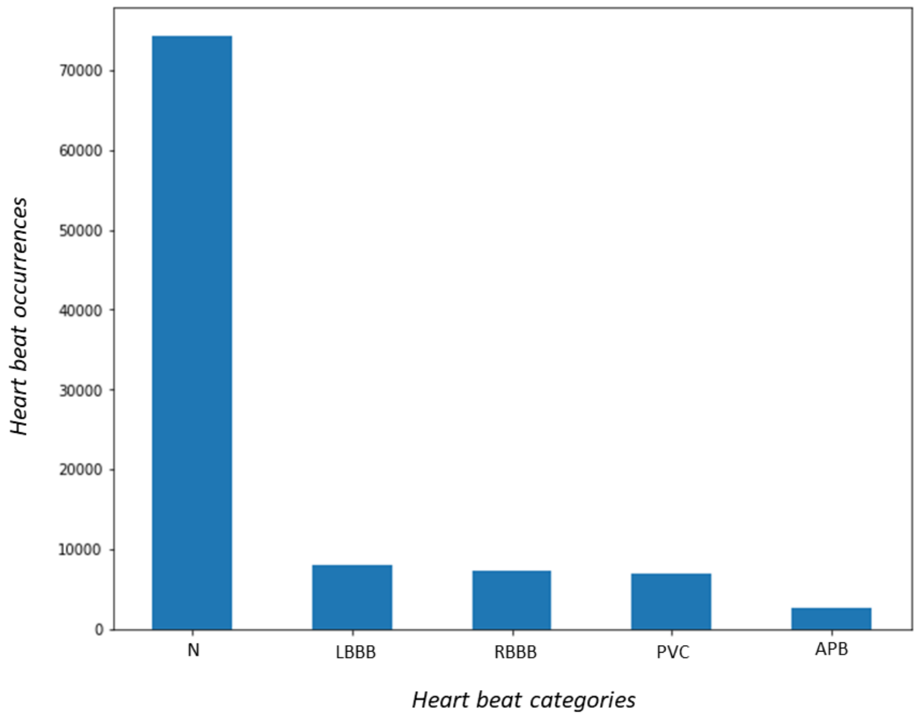

Fig. 3: Count of selected heartbeat types from the MIT-BIH arrhythmia database [46].

Indeed, the compression algorithm—chosen for this work—allowed to involve integer CRs, otherwise, the sensing matrix Φ cannot be defined (see (2)). For simplicity, in this work the *CR*s are chosen in forms of powers of 2 to experiment the maximum number of CRs, *i.e.,* four in this study. Thus, we opted for imposing an initial length of 176 (instead of 179) for each heartbeats. To do so, we performed a cutting of three samples at the extremities of the signal.

An example of a heartbeat signal represented in the uncompressed domain and in its four versions in the compressed domain is depicted in Figure 4.

4.2 Study Results

This section reports the empirical evaluation we conducted to evaluate the classification performances of NEAPOLIS in the compressed domain.

The classification performances—obtained by NEAPOLIS applied to the uncompressed ECG signal and to the 4 versions of compressed ECG signal—have been compared by using the following class-level metrics:

- **Accuracy**, *i.e.,* the number of all the correctly classified instances divided by the total number of the instances. It is computed as $\frac{TP+TN}{TP+TN+FP+FN}$

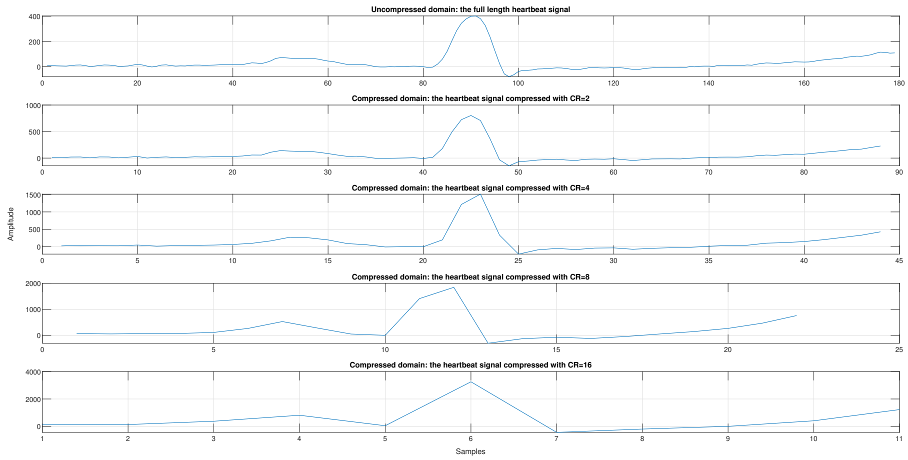

Fig. 4: Example of a heartbeat signal represented in the two domains and for different CRs.

- **Sensitivity**, *i.e.,* the number of positive instances the are correctly classified with respect to the sum between the number of correctly classified positive instances and wrongly classified ones as negative. It is computed as $\frac{TP}{TP+FN}$
- **Specificity**, *i.e.,* the number of negative instances that are correctly classified divided by the sum between the number of negative instances correctly classified and the wrongly classified positive instances, computed as $\frac{TN}{TN+FP}$
- **Precision**, *i.e.,* the number of positive instances that are correctly classified with respect to the total number of positive instances, computed as $\frac{TP}{TP+FP}$
- **F1**, *i.e.,* that represents the harmonic mean of precision and recall, computed as $\frac{2\times TP}{(2\times TP)+FN+FP}$

RQ1: NEAPOLIS for Uncompressed ECG Signals To answer RQ1, we reported the global results — expressed in terms of the above classification metrics — in Table 2. This table compares the previously published version of NEAPOLIS with the refined version presented in this paper. Therefore, this table compares versions of the approach only in terms of application on uncompressed signal. From this results, it is possible to observe that the refined version of NEAPOLIS outperforms the previous version with respect to all the classification metric except for the specificity. These results demonstrate the advantage in refining the features vector to be used as input to the ML classification stage. Specifically, the new set of features—based on the evaluation of the cosine discrete transform—has revealed its impact on the classification performances of NEAPOLIS. The global accuracy achieved by this newly refined version of the NEAPOLIS is $0,989$.

Table 2: Comparison between NEAPOLIS applied to the uncompressed ECG and the previously published version of NEAPOLIS [56].

Version of NEAPOLIS	Sensitivity	Specificity	Precision	F1
Uncompressed - Previous version [56]	0,971	**0,995**	0,972	0,971
Uncompressed - This version	**0,989**	0,986	**0,989**	**0,989**

Table 3: Comparison between NEAPOLIS applied to the uncompressed ECG and NEAPOLIS applied to the compressed ECG according to the specific CR.

Version of NEAPOLIS	Accuracy	Sensitivity	Specificity	Precision	F1
Uncompressed - This version	0,989	0,989	0,986	0,989	0,989
Compressed with CR = 2	0,992	0,992	0,987	0,992	0,992
Compressed with CR = 4	0,992	0,992	0,987	0,992	0,992
Compressed with CR = 8	0,992	0,992	0,989	0,992	0,992
Compressed with CR = 16	0,991	0,991	0,989	0,991	0,991

RQ2: NEAPOLIS for compressed ECG Signals To answer RQ2, we reported the global results of NEAPOLIS in the compressed domain in Table 3. These achievements clearly highlight that the performances of NEAPOLIS on the uncompressed ECG signal are equals to the ones provided by NEAPOLIS when applied to the compressed signal.

Figure 5 contains the boxplots of the classification metrics for all the versions of NEAPOLIS, averaged among the 1,000 iterations.

To provide a complete overview of the results, Figure 4 shows the classification performances detailed by class. These results are in line with the global ones, therefore — also in this case — it is possible to observe that NEAPOLIS shows comparable performances both in the uncompressed than in the compressed domain.

The only variations shown by all the results are mostly provided by the third decimal digit. This could mean that the difference is not significant and that the main result of this work is that NEAPOLIS shows the same potential for application in the uncompressed and compressed domain. However, this slight difference may be due to the filtering operation performed by the DBBD compression algorithm that reduces the effect of noise and distortion on the performed classification.

5 Conclusion and future work

In this paper we presented an extended version of NEAPOLIS, an approach originally designed to provide an accurate and real-time detection of arrhythmia conditions. Once satisfied these requirements, we focused on an extension of that work, with the aim at evaluating the potential of NEAPOLIS to be involved in contexts of compressed ECG.

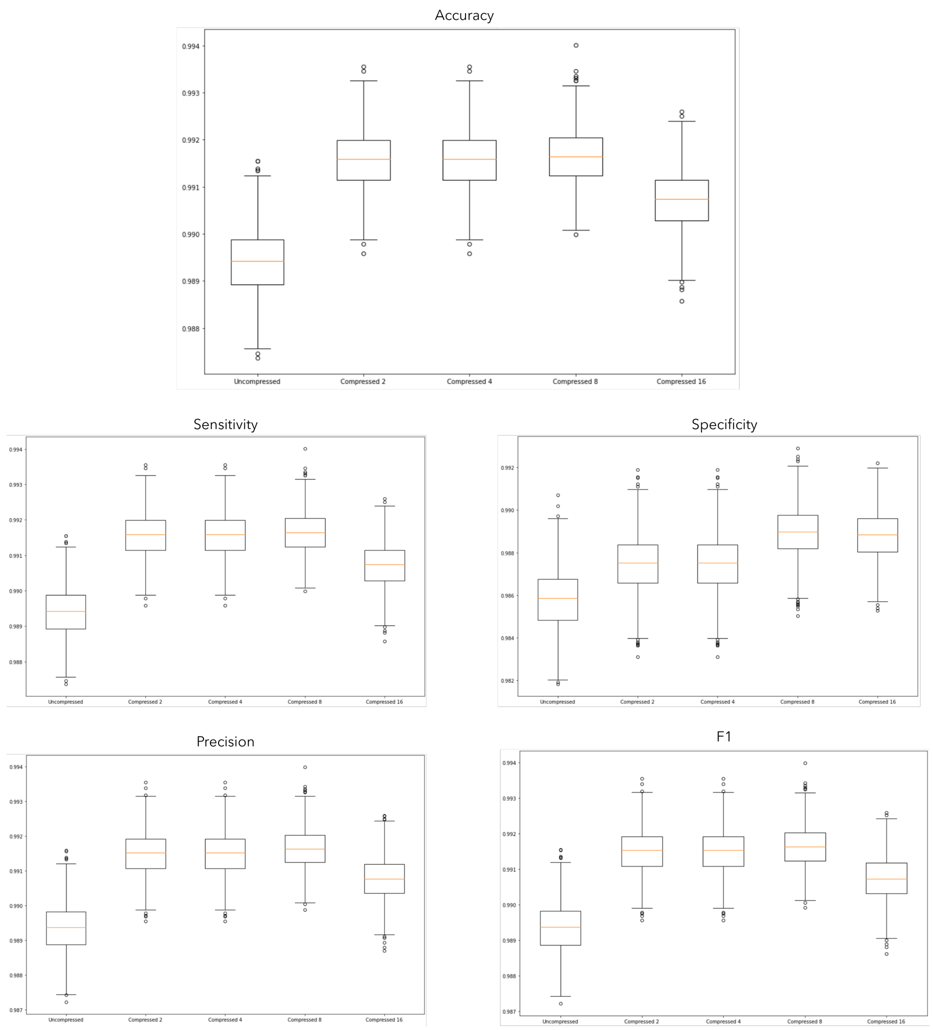

Fig. 5: The boxplots related to the global performances achieved by all the versions of NEAPOLIS.

To this aim, we slightly refined the set of features originally designed for NEAPOLIS and optimized it according to the chosen compression algorithm, *i.e.,* the one based on a Deterministic Binary Block Diagonal matrix as sensing matrix.

An extensive study was conducted to evaluate the potential of NEAPOLIS in the compressed domain; specifically, we evaluated the classification performances of our approach at varying of different Compression Ratios. The final results clearly showed that this new version of NEAPOLIS can work with highly compression ECG signal, by reaching a Compression Ratio of 16.

Table 4: Comparison between uncompressed and compressed NEAPOLIS detailed by class.

NEAPOLIS	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**F1**
Class N - Normal Heartbeat					
Uncompressed	0,991	0,995	0,981	0,994	0,994
CR = 2	0,993	0,996	0,984	0,995	0,995
CR = 4	0,993	0,996	0,984	0,995	0,995
CR = 8	0,993	0,995	0,986	0,995	0,995
CR = 16	0,992	0,994	0,986	0,995	0,995
Class LBBB - Left Bundle Branch Block					
Uncompressed	0,999	0,991	1,000	0,999	0,991
CR = 2	0,999	0,993	1,000	0,999	0,993
CR = 4	0,999	0,993	1,000	0,999	0,993
CR = 8	0,999	0,995	1,000	0,999	0,995
CR = 16	0,999	0,994	1,000	0,998	0,994
Class RBBB - Right Bundle Branch Block					
Uncompressed	0,998	0,986	0,999	0,992	0,989
CR = 2	0,999	0,993	1,000	0,995	0,994
CR = 4	0,999	0,993	1,000	0,995	0,994
CR = 8	0,999	0,991	1,000	0,996	0,994
CR = 16	0,999	0,991	1,000	0,995	0,993
Class APB - Atrial Premature Beat					
Uncompressed	0,993	0,845	0,997	0,892	0,867
CR = 2	0,995	0,868	0,998	0,918	0,892
CR = 4	0,995	0,868	0,998	0,918	0,892
CR = 8	0,995	0,883	0,997	0,902	0,893
CR = 16	0,994	0,890	0,997	0,883	0,886
Class PVC - Premature Vetricular Contraction					
Uncompressed	0,996	0,987	0,997	0,962	0,974
CR = 2	0,997	0,988	0,998	0,973	0,980
CR = 4	0,997	0,988	0,998	0,973	0,980
CR = 8	0,997	0,989	0,998	0,973	0,981
CR = 16	0,997	0,985	0,998	0,970	0,978

As future directions, we aim at performing a more extensive study focused on the impact of the features that compose the features vector of NEAPOLIS in relation to the different Compression Ratios. For example, if a specific feature loses its importance in relation of the compression ratio, it can be removed to lighten the classifier, too.

Furthermore, it could be necessary to conduct a comprehensive evaluation in the context of continuous machine learning, for example with a real-time monitoring IoMT system, to evaluate how the usage of a compressed ECG signal influence the prediction effectiveness and if it can be lead to the concept drift phenomenon.

Finally, we consider also the local prediction as a future line of work. Indeed, NEAPOLIS could be studied also in a local perspective, *i.e.,* with a refined training dataset in order to provide detections more accurate at patient level.

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