Three-class ECG beat classification by ordinal entropies

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Abstract

The automatic and rapid analysis of long-term electrocardiogram (ECG) records still remains a challenging task. Most of the existing algorithms are time consuming and require a training step. In this paper, we present a training free two-level hierarchical model based on ordinal patterns for classifying ECG beats into three types. The classification rules include morphological and temporal properties of the ECG signal that are compared to R-R and QRS dependent thresholds derived from the beat CEOP or PE series. The experimental classification rates obtained from the MIT-BIH Arrythmia database (93.66%) and the St. Petersburg Institute of Cardiological Technics (INCART) database (95.43%), considering the Advancement of Medical Instrumentation (AAMI) recommendations, confirm the ability of the proposed approach for a multi-class classification.

Keywords: Adaptive ECG Classification, Ordinal Entropy, Real-time analysis.

1. Introduction

The diagnosis of heart diseases has generated ongoing interest in the field of biomedical engineering. The most reliable method to depict the electrical waveform propagation in the heart is to use the electrocardiogram (ECG) [1, 2]. To find an appropriate parameter in order to detect arrythmias from the ECG remains an active and relevant research topic [3–5]. This is due to the difficulty to detect generic arrythmia. An interesting survey of the heartbeat classification has been proposed in [6] including signal processing methods, segmentation and learning algorithms. Existing work based on the combination of chaos theory and information theory brought interesting results in the analysis of time series [7, 8], among which entropy based methods like cross-approximate entropy [9], sample entropy [10], cross-sample entropy [11], cross-conditional entropy [12], Shannon entropy of diagonal lines with different lengths in joint recurrence plots [13], permutation entropy [14, 15] and, joint distribution entropy [16] have shown great potential for short-term analysis [17]. However, within multiple work already done on heart disease analysis using entropy measures [18], to the best of our knowledge none of them has succeeded in a specific way in detecting and classifying ECG beats. As highlighted in recent work [19], the ECG beat classification using the AAMI recommendations still remains an open problem. There is still no precise theory regarding the choice of features to identify a particular disease. In [19], the authors proposed a nonlinear data adaptive decomposition method in order to extract features from ECG records.

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Ordinal pattern based entropy algorithms are fast and easy to implement [20, 21]. Statistics on ordinal patterns have been shown to be more effective than indicators of heart rate variability established in order to distinguish patients with congestive heart failure [22]. A recent classification approach of cardiac bio-signals based on the comparison between ordinal patterns and symbolic dynamics features and, conventional heart rate variability parameters revealed that ordinal patterns provide by far the most valuable and non-redundant information about the underlying time series[23]. Additionally, ordinal patterns have also been shown to be useful features for classification of fetal heart condition [24]. Such results thus confirm that ordinal pattern entropies can be efficiently applied to ECG data analysis. Permutation entropy has always been shown to significantly improve the ability to distinguish variability in heart rate under different physiological and pathological conditions [25]. In [26], symbolic dynamics and renormalized entropy were used to detect abnormal heart rate variability in patients who had been classified as low risk using traditional methods. In [27], Zunino et al. used min-entropy permutation to discriminate against patients with atrial fibrilla (AF). Recently in 2018, permutation entropy and min-entropy permutation (PME) were applied in a time series of heartbeats to detect changes in the emotional states of subjects [28].

In the wake of above work, we recently proposed a binary classification algorithm based on two ordinal pattern algorithms, namely the permutation entropy (PE) and the conditional entropy of ordinal patterns (CEOP) [29]. The idea was to distinguish between normal and abnormal ECG beats according to the Association for the Advancement of Medical Instrumentation (AAMI) recommendations. But, in this paper we suggest an extension of that method to three classes in order to further classify abnormal beats. Indeed, the classification of ECG diseases imposes that abnormal beats are themselves classified. As the ECG parameters vary from an individual to another [30], the proposed approach is designed to adapt the record so as to perform patient dependent results. Our algorithm is a two-level hierarchical classification model that does not require prior training. Its efficiency is evaluated on the gold standard MIT-BIH database [31] and the INCART database [6]. Afterwards, the paper is organized as follows: Sect. 2 gives a brief reminder of two ordinal pattern based entropy algorithms, Sect. 3 provides the principle of the proposed approach including the set of features used in this investigation, Sect. 4 discusses the performance analysis of the proposed method and Sect. 5 gives some concluding remarks.

2. Overview of the ordinal pattern based entropy algorithms

2.1. Permutation entropy (PE)

The permutation entropy of order n is the measure of the distribution of discrete probabilities of $n!$ ordinal patterns [32]. The probability distribution is obtained by counting the occurrences of each pattern. For a given time series $\{x_t\}_{t=0,1,...,T-1}$ of length T, the permutation entropy of order n is defined as:

$$H(n) = -\sum p(\theta).\ln(\mu(\theta)), \tag{1}$$

where

$$\mu(\theta) = \frac{\#\{k \mid 0 \leq k \leq T-n, \pi_k = \theta\}}{T-(n-1)}. \tag{2}$$

$\mu(\theta)$ is the probability of the permutation θ, # denotes the cardinality, π_k is the permutation of rank k and $n+1$ the embedding dimension [32]. More details on the PE are given in [33].

2.2. The conditional entropy of ordinal patterns(CEOP)

The CEOP algorithm is fast and can be used for real-time evaluation of time series complexity. Unakafov and Keller also developed a fast algorithm which is available online[1]. Eyebe *et al.* [32] showed

[1]at `www.mathworks.com/matlabcentral/fileexchange/48684-fast-conditional-entropy-of-ordinal-patterns`

that the CEOP of order n can be defined as

$$h(n) = H(s) - H(n), \tag{3}$$

where $H(n)$ is the Shannon entropy of the set of permutations of order n represented as

$$H(n) = -\sum \mu(\theta) \cdot \ln(\mu(\theta)), \tag{4}$$

with

$$\mu(\theta) = \frac{\#\{k \mid 0 \leq k \leq T-n, \pi_k = \theta\}}{T-(n-1)}.$$

Likewise, $H(s)$ is the Shannon entropy corresponding to the series $\{\mathscr{S}\}$ of $n \times 2$ ordinal matrices $\mathscr{S}$.

3. Proposed classification approach

The proposed approach combines two main steps, including segmentation and classification. The segmentation phase is implemented using the built-in defined functions available in physionet [34] and adjusted for the corresponding databases. We used these functions to detect RR segments (considered as ECG beats) and to rebuild QRS complexes. Fig. 1 shows an example of RR segment and QRS complex. Prior to the classification process, the extraction of some ECG features is required.

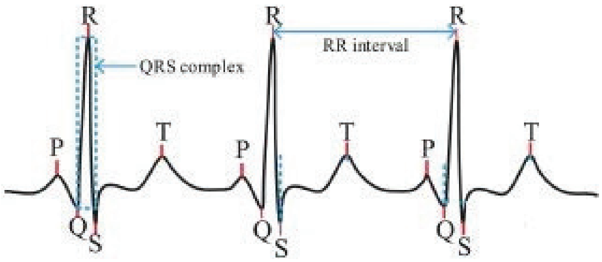

Figure 1: An illustration of *RR* values and QRS complexes.

3.1. Extraction of ECG features

ECG features are obtained by applying scalar transforms to ECG beats or to the whole record. Therefore, we first define the RR segment or ECG beat, noted as $\mathrm{R-R}$, the amplitude variation of the ECG between two consecutive R peaks as a function of time. The first feature is the beat length, that is the length of $\mathrm{R-R}$, noted as RR. RR is the number of samples contained in $\mathrm{R-R}$. For a record containing N RR segments, we agree to set as $\mathrm{R-R}_i$ the i-th RR segment, $0 \leq i \leq N-1$. The corresponding length is noted as RR_i or $RR(i)$.

The second feature is the beat entropy $h_{\mathrm{R-R}}$. The beat entropy is obtained by computing the ordinal entropy using the beat values $\mathrm{R-R}(k)$, $0 \leq k \leq RR-1$. As in the case of $\mathrm{R-R}_i$ length, $h_{\mathrm{R-R}}(i)$ is the entropy of $\mathrm{R-R}_i$.

The third feature is the beat skewness $s_{\mathrm{R-R}}$ and the record skewness s_r (skewness of the whole record). We remind that for a given signal $\{x(k)\}$, the skewness is evaluated using the following formula:

$$s_x = \sum_{k=1}^{L} \left(\frac{x(k) - \overline{x}}{\sigma_x} \right)^3, \tag{5}$$

where L is the length of x, $\bar{x}$ its mean value and σ_x its standard deviation.

Other features like the beat mean value $\overline{\mathrm{R}-\mathrm{R}}$ and the beat standard deviation $\sigma_{\mathrm{R}-\mathrm{R}}$ are also considered. Once these features have been extracted, they are used for defining quantifiers and thresholds that will be used in the classification process.

3.2. *Heartbeat length based quantifiers*

Heartbeat based quantifiers are widely used for beat types differentiation. It has been shown that the shape of QRS complexes, the relative length of $\mathrm{R}-\mathrm{R}$ and the abrupt changes in the map of $\mathrm{R}-\mathrm{R}$ lengths are appropriate for identifying abnormalities and discriminating between heartbeat types [35, 36].

We defined four quantifiers $r_{1,1}$, $r_{2,1}$, $r_{1,2}$ and $r_{2,2}$ that are based on the heartbeat length RR. These dimensionless quantifiers measure the relative fluctuation of the heartbeat length. Consecutive heartbeats are combined to define quantifiers (Fig. 2). We first consider the local relative variation as the ratio between the difference of two consecutive RR values and their mean value as given:

$$r_{1,1}(i) = \frac{RR_i - RR_{i-1}}{0.5(RR_{i-1} + RR_i)}. \tag{6}$$

The second quantifier considers the global variation of the heartbeat duration (fluctuation around the global mean value of the ECG record), but the averaging is locally computed (mean value of two consecutive RR values) and thus gives the following relative fluctuation of the heartbeat rate:

$$r_{2,1}(i) = \frac{\overline{RR} - RR_i}{0.5(RR_{i-1} + RR_i)}. \tag{7}$$

In the third quantifier, the variation between RR values is locally estimated, but the averaging considers the whole record (global averaging), thus leading to:

$$r_{1,2}(i) = \frac{RR_i - RR_{i-1}}{\overline{RR}}. \tag{8}$$

The fourth quantifier considers both the global variation and the global averaging, hence

$$r_{2,2}(i) = \frac{\overline{RR} - RR_i}{\overline{RR}}. \tag{9}$$

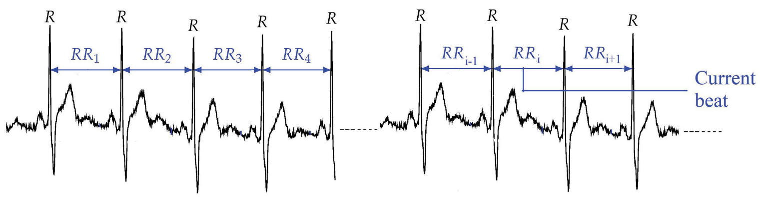

Figure 2: Illustration of $\mathrm{R}-\mathrm{R}$ intervals.

3.3. *Entropy based quantifiers*

Our idea is to determine another type of quantifiers that are to be compared to those presented above for discriminating between heartbeat types. As the duration of the heartbeat has been already used, we adopt another feature using the ECG physiology, namely the beat entropy. We thus define dimensionless entropy based quantifiers for us to be able to compare the behaviour of the two quantifier types. Similarly to the length based quantifiers, we first build the beat entropy series $\{h_{\mathrm{R-R}}(i)\}$ by applying the PE or CEOP to each RR segment $\mathrm{R}-\mathrm{R}_i$. Indeed, for a given order n and RR segment $\mathrm{R}-\mathrm{R}_i$, we determine the set of ordinal patterns as well as the corresponding probability (frequency) distribution and, deduce the beat entropy $h_{\mathrm{R-R}_i}$ or $h_{\mathrm{R-R}}(i)$. An example is given in Fig. 3 where the set of ordinal patterns ($n=3$) as well as the corresponding probability distribution are shown for a given ECG beat. The ECG beat length is $RR=294$ and the corresponding entropy is $h_{\mathrm{R-R}}=2.7662$. For an ECG record containing N beats, the above process is to be repeated for all the beats in order to construct the beat entropy series. Assuming that the minimal beat length corresponds to L samples, we set the embedding dimension $n+1$ (for the PE and CEOP algorithms) such that the condition $L \gg (n+1)!$ is satisfied [20].

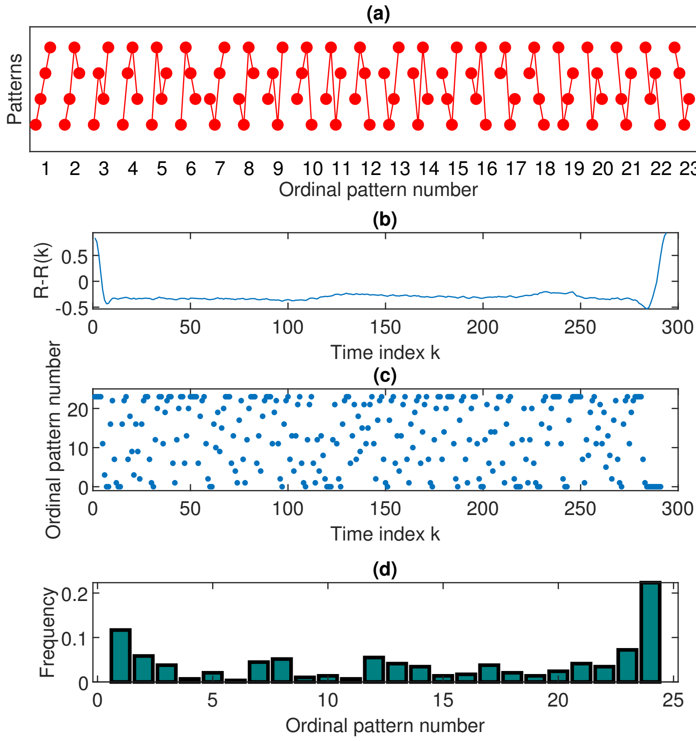

Figure 3: Ordinal pattern distribution for a given RR segment: (a) numbering of the set of ordinal patterns of order $n=3$; (b) R-R representation; (c) ordinal pattern distribution and (d) probability distribution of ordinal patterns for the underlying $\mathrm{R}-\mathrm{R}$.

Once the beat entropy series is determined, we construct the entropy based quantifiers using the same approach as for length based quantifiers. For this purpose, we apply a difference filter to the series of beat entropies and compute the relative filtered beat entropy fluctuation that is to be compared to the relative heartbeat length fluctuation. A difference filter of order m is defined as [29]:

$$G(z)=\sum_{i=0}^{m}(-1)^i \left(\begin{array}{c} i \\ m \end{array} \right) z^{-i}. \tag{10}$$

Let $\{y_{\mathrm{R-R}}(i)\}_{0\leq i\leq N-1}$ be the filtered beat entropy series, $\{y_{\mathrm{R-R}}(i)\}$ is obtained as:

$$y_{\mathrm{R-R}}(i)=\sum_{l=-\infty}^{+\infty} h_{\mathrm{R-R}}(l)g(i-l), \tag{11}$$

where $g(i)$ is the impulse response of the difference filter (inverse z-transform of $G(z)$). We define the relative filtered beat entropy fluctuation as:

$$f_{\mathrm{R-R}}(i) = \frac{|y_{\mathrm{R-R}}(i)| - \overline{|y_{\mathrm{R-R}}|}}{|y_{\mathrm{R-R}}(i)| + \sigma_{|y_{\mathrm{R-R}}|}}, \tag{12}$$

where $\overline{|y_{\mathrm{R-R}}|}$ is the mean value of $\{|y_{\mathrm{R-R}}(i)|\}$ and $\sigma_{|y_{\mathrm{R-R}}|}$ its standard deviation. This relative filtered beat entropy fluctuation is not more than the signal fluctuation ratio already defined in [29]. It represents our first entropy based quantifier and allows to fix problems related to the dependency of the threshold on patients and acquisition systems [29].

The second entropy based quantifier f_{QRS} is determined by considering QRS segments, instead of RR segments. The process is the same as for RR segment case, except that we now consider QRS segments and directly QRS entropy values to compute f_{QRS} as:

$$f_{\mathrm{QRS}}(i) = \frac{h_{\mathrm{QRS}}(i) - \overline{h_{\mathrm{QRS}}}}{h_{\mathrm{QRS}}(i) + \sigma_{h_{\mathrm{QRS}}}}, \tag{13}$$

$\overline{h_{\mathrm{QRS}}}$ being the mean value of $\mathbf{h}_{\mathrm{QRS}} = \{h_{\mathrm{QRS}}(i)\}$.

Once the entropy based quantifiers have been determined, we use them to set threshold values that will help to determine the nature of a given ECG beat.

3.4. Determination of signal-dependent thresholds

The discrimination between beat types is usually made by comparing defined quantifiers to a constant threshold value that is determined using specific rules. In the first stage of our classification process, $r_{1,1}$ and $r_{2,1}$ are to be compared to a threshold value t_{r_1} in order to distinguish N-type beats from the others (abnormal beats). Similarly in stage 2, $r_{1,2}$ and $r_{2,2}$ are to be compared to a threshold value t_{r_2} in order to differentiate between beats of type S and V respectively. Given the fact that the *RR* distribution differs from a patient to another, it is not advisable to set a fixed value of t_{rj}, $j \in \{1,2\}$. We therefore adopt the adaptive threshold approach defined in [29]. This approach which is presented in the forthcoming section takes into account the variations that may occur when moving from one patient to another.

3.4.1. Determination of R-R based threshold

In the first step of the proposed classification approach, heartbeat length based quantifiers are compared with the R-R entropy based quantifier $f_{\mathrm{R-R}}$. For this purpose, series of heartbeat length based quantifiers are compared to single reference value, a threshold value t_{r_1}, that is to be defined from $\{f_{\mathrm{R-R}}(i)\}$. Therefore, we suggest to define t_{r_1} as the weighted absolute mean value of $f_{\mathrm{R-R}}$:

$$t_{r_1} = \alpha_1 \cdot |\overline{f_{\mathrm{R-R}}}|, \tag{14}$$

where the weighting coefficient $0 < \alpha_1 \leq 1$ allows to adjust the threshold value by considering a fraction of $|\overline{f_{\mathrm{R-R}}}|$. Fig. 4 shows an example of beat discrimination for record 106 of the MIT-BIH database. Two values of α_1 were set to show its impact on the discrimination process. It can be observed from this figure that the smaller α_1, the greater the number of beats above t_{r_1}.

3.4.2. Determination of QRS based threshold

We assume that abnormal beats can be classified by identifying particular values in the beat entropy series $\mathbf{h}_{\mathrm{R-R}} = \{h_{\mathrm{R-R}}(i)\}$, beat standard deviation series $\sigma_{\mathrm{R-R}} = \{\sigma_{\mathrm{R-R}}(i)\}$, beat mean value series $\overline{\mathrm{R-R}} = \{\overline{\mathrm{R-R}}(i)\}$, beat skewness series $\mathbf{s}_{\mathrm{R-R}} = \{s_{\mathrm{R-R}}(i)\}$ and the record skewness s_r (skewness of the whole record). By analyzing the behaviour of these features for particular records containing mostly

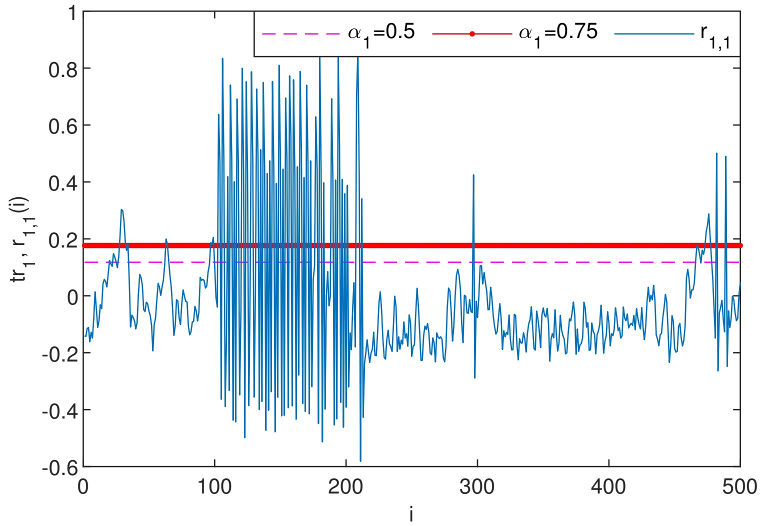

Figure 4: Example of beat discrimination for the first 500 beats of record 106 of the MIT-BIH database. α_1=0.5 (t_{r_1}=0.1178) and α_1=0.75 (t_{r_1}=0.1766). N-type beats are assumed to be those for which $r_{1,1}$ is below the threshold line

abnormal beats, we made some observations and deduced new features that can help discriminating abnormal beats.

For a given record containing N beats, let us consider

$$n_0 = \#\left\{ i \middle| u_1(i) > \min\left(\frac{1}{2}\max(\mathbf{u_0}), \frac{1}{2}\max(\mathbf{u_2})\right)\right\}, \tag{15}$$

where

$$\mathbf{u_0} = \left\{ u_0(i) \middle| u_0(i) = |h_{\mathrm{R-R}}(i) - \overline{h_{\mathrm{R-R}}}|\right\},$$

$$\mathbf{u_1} = \left\{ u_1(i) \middle| u_1(i) = |\sigma_{\mathrm{R-R}}(i) - \overline{\sigma_{\mathrm{R-R}}}|\right\},$$

and

$$\mathbf{u_2} = \left\{ u_2(i) \middle| u_2(i) = |\overline{\mathrm{R-R}}(i) - \sigma_{\overline{\mathrm{R-R}}}|\right\},$$

$0 \le i \le N-1$. n_0 is the set of potentially abnormal beats. Indeed, we observed that $\max(\mathbf{u_0})$ and $\max(\mathbf{u_2})$ are particularly large as compared to $u_1(i)$ for some abnormal beats.

Let us also consider

$$n_{00} = \#\left\{ i \middle| s_{R-R}(i) < 0\right\}, \tag{16}$$

where n_{00} is the cardinality of the set of beats with negative skewness. We noticed that some of such beats with negative skewness are also abnormal. Therefore, we defined the ratio between the set of beats with negative skewness and the set of potentially abnormal beats as

$$r_n = \frac{n_{00}}{n_0}. \tag{17}$$

An example of behaviour for the above features is shown in Fig. 5 obtained with record 106. The highest values indicate possible abnormal beats (S-type or V-type).

We assume that the discrimination between S-type and V-type beats can be realized by defining some intrinsic properties of ECG beats based on the combination of s_r, r_n and $\overline{\sigma_{\mathrm{R-R}}}$. Therefore, we considered

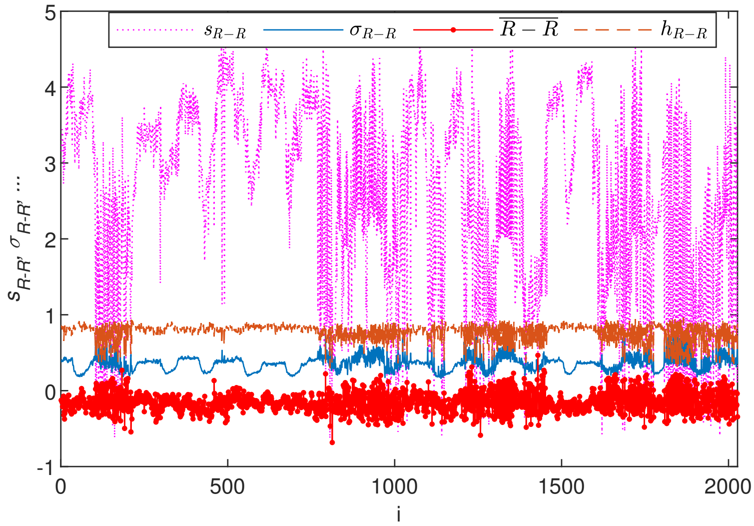

Figure 5: Example of feature estimation with record 106 of MIT-BIH database. Particular beats (potentially abnormal) are those with specific values of the three features: for example $s_{R-R}(i) < 0$ and $\overline{R-R}(i) > 0, \ldots$ For this example, we got $\overline{\sigma_{R-R}} = 0.3582$, $r_n = 1.4423$; and $s_r = 2.4204$.

records 106, 119, 200, 207, 208 223 and 232 of the MIT-BIH database to observe the behaviour of the above features as they contain a large number of abnormal beats. The idea is to point out particular values (values that are either too small or too large as compared to the mean value) of these features for each of these records. By analyzing the corresponding behaviour of s_r, r_n and $\overline{\sigma_{\text{R-R}}}$, we observed two particular cases for which the threshold need to be large and, another case that requires a small threshold value for an efficient beat discrimination. According to this observation, we defined the second threshold t_{r_2} as a nonlinear function such that

$$t_{r_2} = \begin{cases} \frac{1}{\alpha_2} \cdot \sigma_{f_{\text{QRS}}}, & \text{if case 1;} \\ \frac{1}{2\alpha_2} \cdot \sigma_{f_{\text{QRS}}}, & \text{if case 2;} \\ \alpha_2 \cdot \sigma_{f_{\text{QRS}}}, & \text{otherwise.} \end{cases} \tag{18}$$

The case 1 and the case 2 are set as:

Case 1:

$$\Big(s_r < 0 \wedge 0.087 \le \overline{\sigma_{\text{R-R}}} < 0.095 \vee 0.165 \le \overline{\sigma_{\text{R-R}}} < 0.18\Big) \vee \Big(s_r > 0 \wedge 0.085 \le \overline{\sigma_{\text{R-R}}} < 0.09\Big);$$

Case 2:

$\Big(0 < r_n < 1 \wedge 0.23 \le \overline{\sigma_{\text{R-R}}} \le 0.61\Big) \vee \Big(r_n = 0 \wedge \overline{\sigma_{\text{R-R}}} > 0.5\Big) \vee \Big(r_n > 1 \wedge \overline{\sigma_{\text{R-R}}} \ge 0.4 \wedge s_r > 0\Big) \vee \Big(0 < s_r < 1.5 \wedge \overline{\sigma_{\text{R-R}}} \ge 0.145\Big) \vee \Big(s_r < 0 \wedge (\overline{\sigma_{\text{R-R}}} < 0.087 \vee 0.095 \le \overline{\sigma_{\text{R-R}}} < 0.165 \vee \overline{\sigma_{\text{R-R}}} \ge 0.18)\Big) \vee \Big(r_n > 1 \wedge 0.2 \le \overline{\sigma_{\text{R-R}}} < 0.4\Big) \vee \Big(s_r > 0 \wedge (\overline{\sigma_{\text{R-R}}} < 0.085 \vee 0.09 \le \overline{\sigma_{\text{R-R}}} \le 0.145)\Big) \vee \Big(s_r > 0 \wedge \overline{\sigma_{\text{R-R}}} \ge 0.145 \wedge n_0 = 0 \wedge n_{00} \ne 0\Big)$.

By considering the above conditions (case 1 and case 2), the classification of abnormal beats can be undertaken. As in the case of tr_1, $0 < \alpha_2 \le 1$ is a scaling factor or calibration parameter that allows the algorithm to adapt the acquisition system (database) [29]. Indeed, for some ECG records, $\sigma_{f_{\text{QRS}}}$ can be too large or too small, although its dependence on the nature of the record is guaranteed. We therefore adopt to adjust this value such that the threshold matches with the range of the defined quantifiers. Thus, α_j $j \in \{1,2\}$ can be considered as training parameters that are adjusted to obtain a good classification rate. Depending on the nature of the descriptor (RR segment or QRS complex), we set α_1 and α_2 respectively. α_1 is related to RR segments while α_2 is QRS complexes related. For a given database, there is a single value of α_j that should be considered. The optimal value of α_j should correspond to the maximum classification rate, by including all the three beat classes.

3.4.3. Determination of optimal scaling factors α_1 and α_2

The major difficulty for a user is to choose α_1 and α_2 for an optimal classification result while working on an arbitrary database. In order to fix such a difficulty, we propose a theoretical estimate of α_1 for the user to easily adapt the algorithm to an unknown database. As we observed from our previous work in [29] that the value of α_1 is close to 1 and that the classification rate does not significantly depends on this parameter, we suggest that for a given record, a record dependent scaling factor $\alpha_{1,l}$ is approximated as:

$$\alpha_{1,l} = 1 - \sigma_{r_{1,1}} - \sigma_{r_{2,1}} - \sigma_{f_{QRS}}, \tag{19}$$

where index l refers to the record number. Therefore, the optimal value of α_1 for the whole set of records (database) is approximated as:

$$\alpha_{1_{opt}} = 2 \cdot \overline{\alpha_{1,l}} - \sigma_{\alpha_{1,l}}, \tag{20}$$

where $\sigma_{\alpha_{1,l}}$ is the standard deviation of $\{\alpha_{1,l}\}$, and $\overline{\alpha_{1,l}}$ its mean value.

Similarly, we suggest for each record to approximate $\alpha_{2,l}$ as

$$\alpha_{2,l} = \frac{\sigma_{f_{\mathrm{QRS}}}}{\max(r_{2,1})}, \tag{21}$$

hence

$$\alpha_{2_{opt}} = \overline{\{\alpha_{2,l}\}} \tag{22}$$

for the whole database. An approximation error of about ± 0.01 can be considered for improving the sensitivity of S-type beats (Se_S). Indeed, we observed that Se_S increases with α_2; so we expect that adding 0.01 to the computed value of α_2 significantly increases Se_S without affecting the sensitivity of V-type beats (Se_V).

Fig. 6 shows the behaviors of $\alpha_{1,l}$ and $\alpha_{2,l}$, $1 \le l \le 44$, for the CEOP and the PE in the case of the MIT-BIH database. As the value of α_1 does not significantly impact on the classification result, it is also possible to analyze a database by applying individual $\alpha_{1,l}$ to each record instead of the global value α_1.

3.5. Classification of ECG beats

We define three classes of ECG beats according to the AAMI recommendations. Details on the definition of these classes are given in Table 1.

The classification process combines two stages. The first stage is to distinguish N-type beats from the other beats (normal beats from abnormal beats) through a binary classification, while the second one consists in classifying the remaining unclassified beats (abnormal beats) into S-type and V-type. The S and V classes contain the most important arrhythmias.

We considered that a beat is of type N if $r_{1,1} < t_{r_1}$ or $r_{2,1} < t_{r_1}$ while a beat belongs to the sets of S or V-type if this condition is not verified. Similarly, a beat is of type S if $r_{1,2} > t_{r_2}$ or $r_{2,2} > t_{r_2}$, while it is of type V if this condition is not satisfied.

The classification approach can thus be summarized as follows:

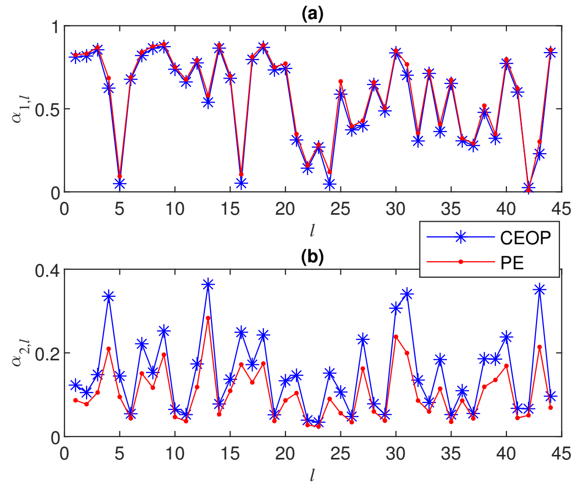

Figure 6: Behaviors of the record training parameters (a) $\alpha_{1,l}$ and (b) $\alpha_{2,l}$ in the case of the MIT-BIH database. The corresponding values for the whole database are respectively $\alpha_{1_{opt}} = 0.8498$ and $\alpha_{2_{opt}} = 0.15$ for the CEOP and, $\alpha_{1_{opt}} = 0.9089$ and $\alpha_{2_{opt}} = 0.1042$ for the PE

Table 1: Beat Annotation for each classification category.

Category	Heartbeat Type	Annotation
Normal (N)	Left Bundle Branch Block	L
	Right Bundle Branch Block	R
	Normal Beat	N
Supraventricular escape beat (S)	Atrial Premature Contraction	A
	Nodal (junctional) Premature Beat	J
	Supraventricular Premature Beat	S
	Aberrated Atrial Premature Beat	a
	Atrial Escape Beat	e
	Nodal (junctional) Escape Beat	j
Ventricular escape (V)	Premature Ventricular Contraction	V
	Ventricular Escape Beat	E
	Others	F, Q, . . .

Algorithm

Stage 1: RR based classification

1. Split an N-beat length signal into beats (RR segments) and compute their PE or CEOP to obtain the beat entropy series $\{h_{\mathrm{R-R}}(i)\}_{0 \leq i \leq N-1}$;
2. Apply $G(z)$ to the series $\{h_{\mathrm{R-R}}(i)\}$ and obtain $\{y_{\mathrm{R-R}}(i)\}$;
3. Deduce from $\{y_{\mathrm{R-R}}(i)\}$ the fluctuation ratio series $\{f_{\mathrm{R-R}}(i)\}$ using Eq. (12);
4. Compute $r_{1,1}$ and $r_{2,1}$ as in Eq. (6) and Eq. (7);
5. Determine t_{r_1} using Eq. (14);
6. If $r_{1,1} < t_{r_1}$ or $r_{2,1} < t_{r_1}$, classify the beat as N-type.

Stage 2: QRS based classification

1. Consider the remaining beats (non N-type beats)

2. Reconstitute each QRS complex by building a 181 length windows centered on the R-peak and compute the corresponding PE or CEOP to obtain the entropy series $\{h_{\text{QRS}}(i)\}$
3. Determine the fluctuation ratio series $\{f_{\text{QRS}}(i)\}$ as in Eq. (13)
4. Compute $r_{1,2}$ and $r_{2,2}$ as in Eq. (8) and Eq. (9)
5. Determine t_{r_2} using Eq. (18)
6. If $r_{1,2} > t_{r_2}$ or $r_{2,2} > t_{r_2}$, classify the beat as S-type.

$r_{j,i} < t_{rj}$ or $r_{j,i} > t_{rj}, (i, j) \in \{1,2\}^2$ allows to distinguish between beats in stage 1 and stage 2 respectively. Further refinement processing based respectively on RR or QRS complex can be undertaken within each stage in order to improve the classification results.

4. Results and discussion

4.1. Experimental data

We used the MIT-BIH Arrhythmia and INCART databases for our experiments. We first vary $0 \leq \alpha_j \leq 1$ by simulation until the maximum classification rate is obtained.

4.1.1. MIT-BIH Arrythmia database

The MIT-BIH arrhythmia database is considered as a gold standard database for arrhythmia [31, 34]. The ECG in this database has been tagged by comments concerning the kind of the heartbeat or the cardiac events. The database contains 48 annotated ECG corresponding to 47 patients (ECG recordings 201 and 202 are from the same patient). The data are sampled at 360 Hz per channel with 11-bit resolution over a $10mV$ range. 23 of the 48 ECG recordings (the ”100 series”) were collected from routine ambulatory practice and, the remaining 25 (the ”200 series”) were selected to include examples of uncommon but clinically important arrhythmia cases that were not well represented in the 23100-series recording. Each record has a duration of 30 min and contains two ECG leads. The first channel was a modified limb lead II (ML II) for all records except for record 114 for which $V5$ was used as the first lead and ML II as the second lead. The leads were then interchanged in the study. The second channel was usually $V1$ (sometimes $V2$, $V4$ or $V5$, depending on subjects). According to the AAMI recommendation, the records containing paced beats were excluded, namely $102, 104, 107$, and 217.

4.1.2. St. Petersburg Institute of Cardiological Technics (INCART)

The INCART database contains 75 annotated records collected from 32 long term ECG (Holter) data. Each record was measured for 30 min and consists of 12 standard leads, each sampled at 257 Hz. The database has approximatively 175000 beats, all of them were independently annotated by an automatic algorithm and then corrected manually by expert cardiologists. The records were extracted from patients experiencing tests for coronary artery disease. None of them had pacemakers, but they had ventricular ectopic beats. The selected recordings of database concerned those of patients that ECG’s consistent with ischemia, coronary artery disease, conduction abnormalities, and arrhythmias. The lead in the MIT-BIH-AR database (lead II) were chosen to realise the experiments exhibited in this work.

4.2. Evaluation of the classification performance

The two databases presented above are imbalanced and the accuracy result might be considered as relying on the large size of some classes. In order to balance all the classes, we consider the J_κ index that includes the J index and the Cohen’s kappa (κ) [37]. The J index allows to better evaluate the effectiveness of a method in discriminating ECG arrhythmias. According to the AAMI standards, the J index is defined as [37]:

$$J = S_{eS} + S_{eV} + P_S^+ + P_V^+, \tag{23}$$

where J ranges from 0 to 4. Only the sensitivities (S_e) and positive predictions (P^+) of the S and V classes are considered as they are supposed to be those covering the most important arrythmia.

Cohen's kappa (κ) is another metric for assessing a classifier performance. It is a performance measure more robust than the average classification rate of imbalanced data set [38]. κ is a metric of compliance that assesses the confusion matrix $C = (c_{i,j})$ (Table 2) and is easily evaluated as:

$$\kappa = \frac{p \sum_1^q c_{i,i} - \sum_1^q T_{r_i} T_{c_i}}{p^2 - \sum_1^q T_{r_i} T_{c_i}}, \tag{24}$$

where $c_{i,i}$ is the cell count in the main diagonal and represents the number of correctly classified elements for the underlying class (true positives), p is the number of elements, q denotes the number of class labels,

$$T_{r_i} = \sum_{j=1}^{q} c_{i,j},$$

and

$$T_{c_i} = \sum_{i=1}^{q} c_{i,j},$$

$1 \leq i, j \leq q$, are respectively the total counts of rows and columns.

Table 2: Model of confusion matrix related to our experimentation. For two distinct labels A and B, X_{A_A} indicates the number of beats of type A normally classified as type A, and X_{A_B} indicates the number of beats of type A classified as type B.

Label	N	S	V	$\sum$	Se
N	X_{N_N}	X_{N_S}	X_{N_V}	$\sum N$	Se_N
S	X_{S_N}	X_{S_S}	X_{S_V}	$\sum S$	Se_S
V	X_{V_N}	X_{V_S}	X_{V_V}	$\sum V$	Se_V
$\sum$	$\sum N_D$	$\sum S_D$	$\sum V_D$	$\sum$	-
P^+	P_N^+	P_S^+	P_V^+	-	-

κ ranges from the random classification ($\kappa = 0$) to the perfect agreement ($\kappa = 1$). A method is said to present a good agreement as $0.61 \leq \kappa \leq 0.80$, and a very good agreement as $0.81 \leq \kappa \leq 1.00$. The combination of both J and κ noted as J_κ takes into account the misclassification and imbalance between the different considered classes [37]:

$$J_\kappa = \frac{1}{2}\kappa + \frac{1}{8} J, \tag{25}$$

where $J_\kappa \in [0,1]$, $J \in [0,4]$ and $\kappa \in [0,1]$. The interpretation of J_κ is then similar to that of the κ index, as both vary between 0 and 1.

4.3. Classification results of the MIT-BIH database

In order to evaluate the efficiency of our method, the classification rate (A_{cc}), the sensitivity (S_e) and the positive predictive value (P^+) are considered. We analyzed a set of 89880 N-type beats, 3026 S-type beats and 7827 V-type beats. By using the CEOP and the PE of order $n = 4$ for the first step and $n = 3$ for the second step, and a difference filter of order $m = 4$, we obtained the results in Table 3. These results correspond to the maximum classification rate obtained after varying α values from 0 to 1 by step size of 0.01. The maximum classification rate $\beta = 93.72$ occurs for $\alpha_1 = 0.86$ and $\alpha_2 = 0.14$ in the case of the CEOP, while $\beta = 92.86\%$ is obtained for $\alpha_1 = 0.9$ and $\alpha_2 = 0.1$ in the case of the PE.

Fig. 7 shows the behavior of the sensitivity for the CEOP and the PE respectively, from where the low sensitivity of the PE for the detection of S-type beats is confirmed. It appears from Table 3 that the results

Table 3: Classification results

Method	$\beta(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	93.72	93.72	93.36
PE	92.86	92.86	91.87

Table 4: Evaluation metrics by class.

	N		S		V	
Method	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	97.65	95.90	61.83	80.79	60.87	69.06
PE	98.12	94.56	20.45	59.01	60.38	73.67

Table 5: Confusion matrix for the best configuration of the CEOP in the case of MIT-BIH database

Label	N	S	V	$\sum$
N	87768	328	1784	89880
S	805	1871	350	3026
V	2946	117	4764	7827
$\sum$	91519	2316	6898	100733

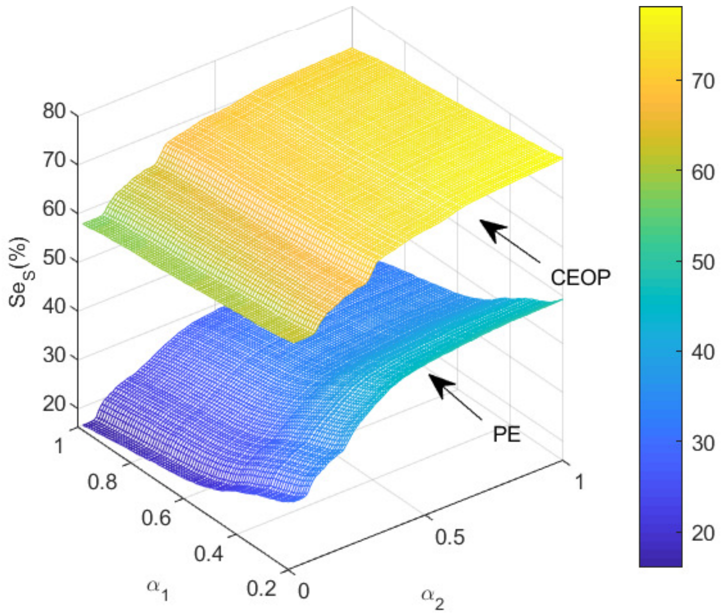

Figure 7: Behavior of the sensitivity of the CEOP and the PE to the detection of S-Type beats (Se_S) in terms of α_1 and α_2.

of the CEOP of order $n = 4$ are relatively better than those of the PE of the same order. Thus, the CEOP discriminates S-type and V-type beats better than the PE in the case of the MIT-BIH database. Such a result is confirmed in Table 4 where the values of each evaluation metric are shown by class. These results are deduced from the confusion matrix presented in Table 5 from which it is also deduced $\kappa = 0.6573$,

$J = 2.7255$ and $J_\kappa = 0.6693$. The value of J_κ attests that although the MIT-BIH database is imbalanced, our method presents a good performance.

By comparing the values of α_1 and α_2 corresponding to the maximal classification rate β to those $\alpha_{1_{opt}}$ and $\alpha_{2_{opt}}$ obtained by applying Eqs. (19)-(22) to the MIT-BIH database, it appears that the two sets of scaling factors are close. Indeed, $\alpha_1 = 0.86$ and $\alpha_{1_{opt}} = 0.8498$, $\alpha_2 = 0.14$ and $\alpha_{2_{opt}} = 0.15$ for the CEOP; while $\alpha_1 = 0.9$ and $\alpha_{1_{opt}} = 0.9089$, $\alpha_2 = 0.1$ and $\alpha_{2_{opt}} = 0.1042$ for the PE. The classification results corresponding to these values of $\alpha_{1_{opt}}$ and $\alpha_{2_{opt}}$ are respectively $A_{cc} = 93.72\%$, $Se_S = 61,53\%$, $Se_V = 61.00\%$, $P_S^+ = 81.27\%$ and $P_V^+ = 68.97\%$ for the CEOP, and $A_{cc} = 92.85\%$, $Se_S = 19.96\%$, $Se_V = 60.51\%$, $P_S^+ = 59.33$ and $P_V^+ = 73.47\%$ for the PE. By applying $\alpha_{2,l}$ for the classification of each record, these results slightly decrease as the algorithm is sensitive to $\alpha_{2,l}$ and its value considerably varies from a record to another. An example is given for the CEOP for which we found $A_{cc} = 93.70$, $Se_S = 58,43\%$, $Se_V = 62.00\%$ and $P_S^+ = 83.51\%$.

4.4. Classification results of the INCART database

In the INCART database, we analysed a set of 153583 N-type beats, 2052 S-type beats and 20238 V-type beats. As in the case of the MIT-BIH database, we used the CEOP and the PE of order $n = 4$ for the first step and $n = 3$ for the second step and, a difference filter of order $m = 4$. The corresponding confusion matrix is shown in Table 6 from which are deduced the results in Tables 7 and 8. These results correspond to the maximum classification rate obtained by varying α values. We obtained as maximum classification rate $\beta = 95.34\%$ for $\alpha_1 = 0.74$ and $0.02 \leq \alpha_2 \leq 0.06$ in the case of the CEOP and, $\beta = 95.65\%$ in the case of the PE for $\alpha_1 = 0.77$ and $0.02 \leq \alpha_2 \leq 0.03$.

Table 6: Confusion matrix for the best configuration of the PE in the case of the INCART database

Label	N	S	V	Σ
N	151424	0	1811	153583
S	218	0	1834	2052
V	3809	0	16429	20238
Σ	155799	0	20074	175873

Table 7: Classification results for the maximal classification rate

Method	$\beta(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	95.34	95.34	–
PE	95.65	95.65	–

Table 8: Evaluation metrics by class for the maximal classification rate.

	N		S		V	
Method	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	98.59	97.29	0	–	80.33	80.34
PE	98.88	97.37	0	–	80.79	82.17

The results obtained for the PE in that case were very close to those of the CEOP. However, we can observe that the maximum classification rate in that case is obtained for two classes, namely N and V, where the algorithm is less sensitive to S-type beats. Such a mismatch suggests that the the properties of S-type beats are updated. Contrarily to the case of the MIT-BIH database for which the optimal value of α_2 corresponds to the maximal classification rate ($A_{cc} = \beta$), we need to determine the optimal value of α_2 for the INCART database. Indeed, there is a compromise between the sensitivity of the algorithm to S and V-type beats that can be balanced by adjusting α_2. Although $Se_S = 0$ for $A_{cc} = \beta$ in the case of the INCART database, it should be pointed out that it increases up to $Se_{S_{max}} = 90.89\%$ ($Se_V = 4.8325\%$, $\alpha_2 \geq 0.95$) for the CEOP and $Se_{S_{max}} = 91.52\%$ ($Se_V = 2.18\%$, $\alpha_2 \geq 0.77$) for the PE.

By applying Eqs. (19)-(22) to the INCART database, we found $\alpha_{1_{opt}} = 0.7447$ and $\alpha_{2_{opt}} = 0.1520$ for the CEOP, and $\alpha_{1_{opt}} = 0.8068$ and $\alpha_{2_{opt}} = 0.0986$ for the PE. The corresponding sensitivities for the S-type beats are respectively $Se_S = 56,04\%$ for the CEOP and $Se_S = 51.51\%$ for the PE, thus confirming the efficiency of the proposed formula for determination of optimal scaling factors. The other classification results are respectively $A_{cc} = 95.23\%$, $Se_V = 73.61\%$, $P_S^+ = 45.87\%$ and $P_V^+ = 84.16\%$ for the CEOP, and $A_{cc} = 95.61\%$, $Se_V = 74.79\%$, $P_S^+ = 47.72\%$ and $P_V^+ = 86.58\%$ for the PE.

By applying individual values of $\alpha_{1,l}$ to each record and adding an approximation error of 0.01 to the computed value of α_2, we obtained the results in Table 9. These results confirm the robustness of the algorithm to the variation of α_1, as well as its high sensitivity to α_2. In that case, the overall results are

Table 9: Evaluation metrics by class for variable $\alpha_{1,l}$, $1 \leq l \leq 75$, in the case of INCART database. We set $\alpha_2 = 0.162$ for the CEOP and $\alpha_2 = 0.1086$ for the PE. The corresponding classification rates are respectively 94.84% for the CEOP and 95.11% for the PE

	N		S		V	
Method	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	97.80	97.74	64.62	43.23	75.39	79.75
PE	98.00	97.82	62.96	43.08	76.43	81.34

much better than those obtained with the MIT-BIH database for both the CEOP and the PE. We can also observe that the values of α_1 and α_2 that give satisfactory classification rates and good sensitivity values for all the three classes in the two databases are approximately the same. Given that the INCART database is also imbalanced, we evaluated the performance of our method in the case of the above parameter setting and found $J_\kappa = 0.7136$ in the case of the CEOP and $J_\kappa = 0.7182$ in the case of the PE, thus confirming its good performance.

α_1 and α_2 are the two training parameters of our algorithm. They are deduced respectively from Eq. (19) and Eq. (21), after extraction of ECG features from a large set of ECG records (or a database). However, the result obtained above for the two databases confirm that these two training parameters are too close for the MIT-BIH and the INCART databases, suggesting that they can be set as constant parameters for any database.

It should also be pointed out that the maximum classification rate does not necessarily correspond to the best result in terms of the abnormality classification. The optimal result corresponds to the highest sensitivity of the algorithm to all the three classes and the corresponding classification rate is smaller than the maximum value. By setting $\alpha_1 = 0.8$ and $\alpha_2 = 0.16$ for the CEOP and, $\alpha_1 = 0.8$ and $\alpha_2 = 0.11$ for the PE in both the MIT-BIH and the INCART databases, we obtain approximately the same results (see Table 10). Such an observation suggests that for an unknown database, the training step may be skipped.

The results in Table 10 are assumed to correspond to our best configuration. In the case of the MIT-BIH database, it appears that the PE is less suitable for the classification of S-type beats, while in both databases the CEOP gives satisfactory results for all the three classes. Fig. 8 presents some examples of sensitivity of the classification rates in terms of the training parameters α_1 and α_2. This figure confirms that our algorithm is less sensitive to α_1 and that the maximum classification rate occurs for approximately the same values of α_2 for both databases.

Table 10: Optimal classification result obtained with a constant parameter setting for both databases: $\alpha_1 = 0.8$, $\alpha_2 = 0.16$ for CEOP; and $\alpha_1 = 0.8$, $\alpha_2 = 0.11$ for PE.

		N		S		V	
Method /database	A_{cc}	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP / MIT-BIH	93.66	97.51	96.01	62.52	77.99	61.39	68.44
PE / MIT-BIH	92.76	97.84	94.75	21.41	54.92	61.90	71.88
CEOP /INCART	95.12	98.68	97.18	62.38	44.09	71.54	85.07
PE /INCART	95.43	98.93	97.31	63.60	42.77	72.10	87.48

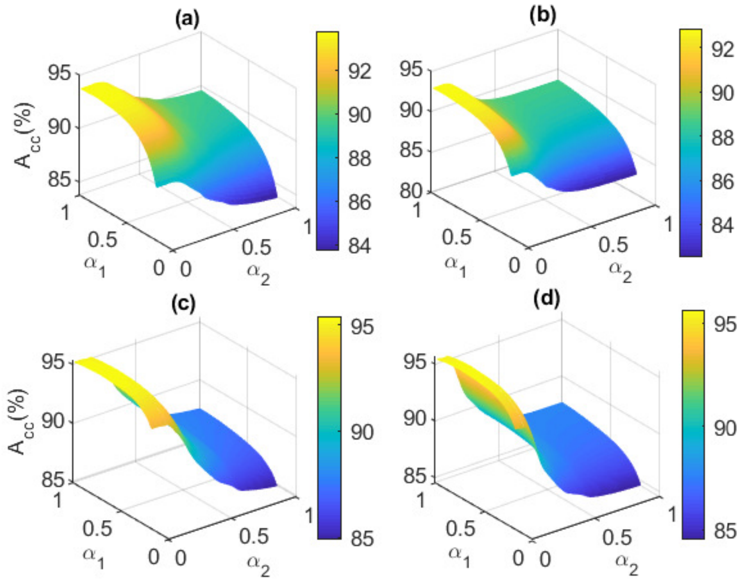

Figure 8: Sensitivity of the classification rate (A_{cc}) in terms of the training parameters α_1 and α_2: case of MIT-BIH database for (a) CEOP and (b) PE; and case of INCART database for (c) CEOP and (d) PE.

4.5. Comparison with other methods

The purpose of this section is to compare the results of our approach with other classification methods also using the MIT-BIH and the INCART databases. All these methods chosen include the learning step applied to half the database for efficient classification. In [39], [40] and [41] the weighted Linear Discriminant was used to achieve the classification. The algorithm in [39] used RR segments as features. In [40], the wavelet transform was used while the temporal and morphological ECG-Intervals were combined in [41] to classify beats into four classes. Meanwhile, a pyramid model in which beats were discriminated into two groups, namely S and N, was used in [42]. Subsequently, a set of classifiers was used to classify each group obtained.

According to Tables 11 and 12, our proposed method particularly well performs the classification of N, S and V-type beats. It presents better performances in terms of the overall accuracy, the positive predictive value and the sensitivity of N and S-type beats as compared to the other methods. Nevertheless, it should be pointed out that the classification results of our method were evaluated on the whole database whereas, the performance of the other methods that stood comparison in this paper were assessed using half the database. Moreover, the intrinsic properties of ECG beats were set using some records of the

MIT-BIH database and successfully tested on a different database, which suggests the generalization of such properties to other databases. By considering the constant setting of the training parameters α_1 and α_2 proposed here to be also an intrinsic property of ECG data and, as they remain quite unchanged for the two databases, our algorithm is supposed to be training free for its application to any other ECG database. Nonetheless, such an assumption is to be further confirmed using other databases in our upcoming research work.

Table 11: Comparison results for the MIT database

		N		S		V	
Method	A_{cc}	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	93.66	97.51	96.01	62.52	77.99	61.39	68.44
PE	92.76	97.84	94.75	21.41	54.92	61.90	71.88
Lin and Yang [39]	93.00	91.00	99.00	81.00	31.00	86.00	73.00
He[42]	91.50	92.00	99.00	91.00	35.00	89.00	81.00
Chazal[40]	89.00	86.90	99.20	75.90	38.50	77.70	81.90
Mariano[41]	78.00	78.00	99.00	76.00	41.00	83.00	88.00

Table 12: Comparison results for the INCART database.

		N		S		V	
Method	A_{cc}	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$	$S_e(\%)$	$P^+(\%)$
CEOP	95.12	98.68	97.18	62.38	44.09	71.54	85.07
PE	95.43	98.93	97.31	63.60	42.77	72.10	87.48
Mariano [41]	91.00	92.00	99.00	85.00	11.00	82.00	88.00
He [42]	90.00	90.30	99.30	79.40	15.40	87.00	72.70

4.6. Speed performance

In this section, we compared the execution time of our algorithm with that of learning based methods, in particular the SVM approach implemented in [43]. We used a 64-bit computer with 8 GB of RAM and Intel core i5 processor to assess the execution time on the MIT database. The table below summarizes the speed performance for each method.

Table 13: Speed performance of the proposed method.

Method	$Speed(Mbps)$
PE	506.25
CPE	405.49
Mondéjar et al. [43]	57.64

It appears from this table that our algorithm is approximatively 10 times faster than the SVM based algorithm in [43]. This can be justified by the individual speed performance of ordinal pattern methods and, the simplicity of our classification method. Our approach directly analyzes data without the need of prior learning, thus attesting its ability for real-time data analysis. The above running speeds were obtained with non-optimized algorithms.

5. Conclusion

In this paper, we proposed an approach based on ordinal pattern entropies for the classification of ECG beats into three classes, namely N, S and V. The method extends our previous algorithm for a binary classification of ECG beats using ordinal patterns. This extension into three classes is made possible by considering some specific properties of S and V-type beats as well as QRS complexes as features, in addition to RR segments already used previously. The results obtained with the MIT-BIH and the INCART databases exhibit a good performance of the proposed algorithm as compared to other classification methods. The set of abnormal beats has been classified into S-type and V-type beats which may further contribute to classifying ECG pathologies. The classification process has been divided into two main stages: the first one consists of separating N-type beats from abnormal beats using R-R based thresholds while, the second stage consists of classifying abnormal beats into S-type and V-type beats respectively using QRS based thresholds. The proposed approach has shown good performance in terms of classification results and running speed. Thus, we further intend to apply it to real-time ECG analysis and, extend it to four classes which may increase its ability for classifying specific pathologies.

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