Effectiveness of morphological and spectral heartbeat characterization on arrhythmia clustering for Holter recordings

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ABSTRACT

Heartbeat characterization is an important issue in cardiac assistance diagnosis systems. In particular, wide sets of features are commonly used in long term electrocardiographic signals. Then, if such a feature space does not represent properly the arrhythmias to be grouped, classification or clustering process may fail. In this work a suitable feature set for different heartbeat types is studied, involving morphology, representation and time-frequency features. To determine what kind of features generate better clusters, feature selection procedure is used and assessed by means clustering validity measures. Then the feature subset is shown to produce fine clustering that yields into high sensitivity and specificity values for a broad range of heartbeat types.

Keywords Clustering methods, Feature extraction, Signal analysis

1. INTRODUCTION

As a tool for clinical settings and medical information management, the diagnosis of transient and infrequent cardiac arrhythmias is employed, usually carried out over long term electrocardiographic signals (Holter ECG) holding a huge amount of heartbeats.¹ Since manual analysis and inspection of a whole Holter recording is a time consuming and exasperating task, then, heartbeat analysis should be provided through an automatic system. Among other important aspects to take into consideration, a proper heartbeat characterization must be ensured as a starting point for reducing the computational burden but achieving compact and consistent groups. Therefore, the effectiveness of extracted heartbeat feature set for heartbeat clustering should be strongly considered. This issue has been addressed before using techniques based on either improved clustering or feature selection/extraction, by instance in.²

Among the known baseline projection approaches, Principal Component Analysis (PCA) and the $Q - \alpha$ algorithm are recommended for feature selection analysis over a wide set of features for separation of heartbeats in long-term ECG signals, as discussed in.¹ In both cases, the original representation space is projected onto a new space preserving the relevant information in terms of an explained variance criterion. However, they ignore the relationship matching the projected space with the original feature space that may supply additional information. Furthermore, a proper relevance analysis for feature selection taking advantage of this relationship might provide an insight on how the underlying data information is to be associated, for example, using different cluster separability and/or compactness measures, even more, identification of most suitable features for heartbeat clustering might be provided by considering validity measures.

Based on clustering measures, this work discusses the effectiveness of commonly used features for heartbeat clustering. To this end, we suggest linear combination of the leading eigenvectors of the covariance matrix as a relevance vector, pointing out the address of the features holding the most discriminating evidence.³ In particular, we consider two basic principles of feature generation: morphological (derived from heart rate variability (HRV) and prematurity) and spectral-based parameters. Extracted from the latter generation principle, besides conventional Fourier, Discrete Wavelet Transform (DWT), and Hermite coefficients, we also use some here introduced features, namely parameters of a cosine modulated Gaussian atom. Experimental testing is provided using the MIT-BIH Arrhythmia Database. A total set of 181 features is considered to be further selected, in terms of provided relevance analysis. The overall feature selection procedure requires

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manual setting of optimal parameters, to this end, validity clustering measures Adjusted Rand Index (ARI)⁴ and Normalized Mutual Information (NMI),⁵ are used as criteria for experimental tuning. And selected feature ensemble is assessed by means of sensitivity and specificity measures, so the underlying pathology discrimination can be further analyzed.

This paper is organized as follows: Section 2 outlines the methods for heartbeat characterization as well as for feature relevance analysis. In sections 3 and 4 the experimental setup is described and results are discussed, respectively. Finally, conclusions and final remarks are presented in Section 5.

2. MATERIALS AND METHODS

2.1 Heartbeat Feature Generation

Morphological features: Heartbeats are usually discriminated by means of morphology, since most pathologies exhibit time-domain changes that are not consistent with normal heartbeats. At first, HRV-based features are considered as a discriminating parameter, specifically to deal with premature ventricular heartbeats as they have high shape similarity with normal heartbeats, but differ in timing and phase of the main fiducial points.¹ Thereby, three HRV-based features are considered,

$$x_1 = r_j - r_{j-1}, \quad x_2 = r_{j-1} - r_{j-2}, \quad x_3 = r_{j+1} - r_j,$$

where r_j is the j -th R-peak time location, and x_1 is the R to R interval, x_2 is the previous R to R interval and x_3 the posterior R to R interval.

Heart rate changes are not only characterized by RR intervals, differences between consecutive heartbeats are also considered as features, as the RR interval information of RR has been already introduced above, only the Atrial P wave morphology index, which is sensible to any increase in heart rate is used,

$$x_4 = \left(\frac{x_3}{x_1}\right)^2 + \left(\frac{x_2}{x_1}\right)^2 + \left(\frac{1}{3} \sum_{i=1}^3 x_i^2 \log(x_i)^2\right).$$

Lastly, the following subset of 3 morphological based features are used: x_5 the dynamic time warping (DTW) dissimilarity index, x_6 polarity of QRS complex and x_7 the energy of QRS complex. In addition the minimum to maximum ratio and variance of the QRS complex are added as features $x_8 = \tilde{q}$ and $x_9 = \text{var}\{\mathbf{q}\}$, where vector $\mathbf{q}$ is the QRS complex at hand, and $\tilde{z}$ is defined as

$$\tilde{z} = \frac{\min(\mathbf{z})}{\max(\mathbf{z})},$$

where $\mathbf{z}$ is a time-series feature vector, such as wavelet coefficients and min and max are the minimum and maximum amplitude values of vector $\mathbf{z}$, respectively.

Spectral-based Features: Even though morphological and time domain features are discriminating attributes of most heartbeats, some pathological heartbeats are not represented by the previous feature subset, spectral attributes such as Fourier coefficients and Hermite basis functions⁶ are used to give information derived from the frequency behavior of the signals. Namely, features $x_{10}, \dots, x_{14}$ correspond to the first five fourier coefficients (ranging from 1 to 20 Hz) and features $x_{15}, \dots, x_{25}$ are the Hermite coefficients, estimated from the QRS complex spectra as recommended in.⁶

The DWT coefficients are considered regarding they provide with information about the spectral changes in different frequency bands of the ECG signal.⁷ In particular, the second order Daubechies wavelet (DB_2) is used given its shape similarity with normal heartbeats. Most information of ECG signals is contained in low frequency bands, namely 0.1Hz to 30Hz, hence an appropriate level for DWT must be chosen. The DWT is performed over fixed length QRS complexes so the number of coefficients is constant over all considered heartbeats. Thereby for the DB_2 wavelet, which has a central frequency of $f_c = 0.66667\text{Hz}$ the subset of features $\{x_{26}, \dots, x_{164}\}$ is generated, and related with specific spectral bands as shown in Table 1.

In addition, the minimum to maximum ratio of each vector of coefficients is also calculated as features $x_{165}, \dots, x_{170} = \{\tilde{A}_5, \tilde{D}_5, \dots, \tilde{D}_1\}$ and variances $x_{171}, \dots, x_{176} = \{\text{var}\{A_5\}, \text{var}\{D_5\}, \dots, \text{var}\{D_1\}\}$. Lastly, a cosine modulated gaussian atom reconstructing the ECG signal is also considered. In particular, derived from the QRS complex spectrogram the

Table 1: Frequency Bands Distribution for DWT-DB₂

Coefficients	Level	Range(Hz)	Features
Detail	1	120 – 240	$x_{99}, \dots, x_{164}$
	2	60 – 120	$x_{65}, \dots, x_{98}$
	3	30 – 60	$x_{48}, \dots, x_{64}$
	4	15 – 30	$x_{38}, \dots, x_{47}$
	5	7.5 – 15	$x_{32}, \dots, x_{37}$
Approximation	5	0 – 7,5	$x_{26}, \dots, x_{31}$

following parameters are extracted: amplitude x_{177} , frequency x_{178} , phase x_{179} , delay x_{180} , and support or duration x_{181} , as suggested for the decomposition of the heart sound signal in.⁸ Therefore, a total set of $p = 181$ features are considered to be further reduced in terms of relevance analysis.

Finally, Table 2 shows a brief summary of the considered subsets of features and their corresponding cardiological target,

Table 2: Features Summary and cardiological target

Features	Description		Target
x_1 to x_4	RR intervals	Morphological	Premature Heartbeats
x_5 to x_9	QRS complex		Abnormal QRS complexes: Extrasystole, block branches.
x_{10} to x_{14}	Fourier Coefficients	Spectral	Right and left bundle branch blocks
x_{15} to x_{25}	Hermite Basis Coefficients		Premature Ventricular Contractions
x_{26} to x_{76}	Wavelet		Paced and fusion beats
x_{77} to x_{181}	Cosine modulated Atom		

2.2 Relevance of Generated Heartbeat Features

As discussed in,³ for a data-set $\mathbf{X} \in \mathbb{R}^{n \times p}$, where n is the number of frequency bins and p the number of time samples, it is possible to find a set of weight values, namely relevance vector, with the main purpose of enabling an effective data dimensionality reduction with a proper quantitative ranking. This can be accomplished in an PCA-similar approach using the least squares function, called MSE-based relevance.

For a feature matrix $\mathbf{X}$ the feature relevance vector can be computed by means of the SVD of its covariance matrix $\mathbf{C}_X = \mathbf{X}^\top \mathbf{X}$, so let,

$$\mathbf{C}_X = \mathbf{V} \mathbf{W} \mathbf{V}^\top$$

where $\mathbf{V} = \{\mathbf{v}_i, i \in p\}$ is the eigenvector matrix and $\mathbf{W} = \{w_1 \geq w_2 \geq \dots \geq w_i \geq w_p, i \in p\}$ is a diagonal eigenvalues matrix. The relevance vector $\mathbf{w} = \{w_i : i \in p\}$ is given by,³

$$\mathbf{w} = \mathbf{E}\{v_i(\bar{\mathbf{v}}_i \circ \bar{\mathbf{v}}_i) : \forall i = 1 \dots, p\}$$

Notation $\mathbf{E}\{\cdot\}$ stands for expectation operator, which is assumed as simple average in this case.

Now, let us introduce a lower dimension parameter $0 < \chi < 1$, such that the following vector of indexes $\mathbf{h}$ is given,

$$\mathbf{h} = \arg \underset{i}{(w_i > \chi; i = 1, \dots, p)} \quad (1)$$

dimensionality reduction can be achieved by selecting only those features, i.e. the h -th indexed features, with a normalized relevance value higher than a predefined (manually set) χ .

Now it can be seen that while PCA aims to find the linear projection $\mathbf{Y} = \mathbf{X} \mathbf{V}$, where $\mathbf{Y} \in \mathbb{R}^{n \times \rho}$ and $\rho < p$, MSE relevance uses the eigenvalues of the covariance matrix to provide with a weight value to each feature holding the initial space. This allows to maintain the interpretability of the classification features instead of PCA where interpretability is lost in the projection. Now, this process becomes a feature selection methodology when a reduced number of eigenvectors and their respective eigenvalues is used.

3. EXPERIMENTAL SET-UP

3.1 ECG Database and preprocessing

The data collection from MIT-BIH is provided with a wide range of heartbeat types in a set of 48 recordings, each one sampled at rate of 360 Hz and lasting 30 minutes long.⁹ A subset of 18 recordings with a variety of cardiac phenomena and both balanced and unbalanced classes was chosen, namely records: 104, 106, 107, 109, 114, 116, 119, 203, 205, 208, 210, 214, 215, 217, 221, 228, 231, 233. Additionally the labels of each heartbeat are provided to the corresponding annotation code: **Normal**, **Left-bundle branch block**, **Right bundle branch block**, **Ventricular contraction**, **Fusion of ventricular and normal**, **fusion of paced and normal** and **Paced**. As regards the preprocessing stage, each recorded holter ECG signal, $s(t)$ is initially subject to discrete transformation, that is, $\mathbf{s} = \{s_n\}$ where $n \triangleq s[nT_s]$, being $n \in \mathbb{N}$ and $T_s = 1/F_s$ the sampling period. Then, to prevent biasing the obtained ECG vector is normalized with the standard score (*z-scores*) approach, i.e.,

$$\hat{\mathbf{s}} = \frac{\mathbf{s} - \mathbf{E}\{\mathbf{s}\}}{\text{var}\{\mathbf{s}\}}. \quad (2)$$

Afterwards, the unbiased vector $\hat{\mathbf{s}}$ is filtered to reduce interferences from power line and base line wander, according to the procedures given in¹⁰ and¹¹ respectively.

3.2 Effectiveness Estimation of Heartbeat Feature Set

Each recording contains annotations of the r -peaks (r_j time locations, where $j = 1, \dots, n$ of all heartbeats in signal $\hat{\mathbf{s}}$. Feature extraction was performed over fixed length signal portions containing the QRS complex, that is, a rectangular window of length 300ms centered at r_j . Hence a feature matrix $\mathbf{X} \in \mathbb{R}^{n \times p}$ where $p = 181$ is the number of features distributed as explained in section 2.

Now for a given input feature matrix $\mathbf{X}$, it is necessary to identify the features that better discriminate the classes within, hence an heuristic search over the parameters ρ and χ is performed. Now to each pair of values, a relevance vector is generated and consequently a subset of features. Finally, the reduced data-set $\hat{\mathbf{X}} \in \mathbb{R}^{n \times \hat{p}}$ where $\hat{p}$ is the total of indexes contained in vector $\mathbf{h}$, i.e. the reduced number of features, is grouped by means of clustering algorithms and validity measures (ARI and NMI) are computed. This process is summarized in Algorithm 1

Algorithm 1 Search of optimal $\hat{\rho}$ and $\hat{\chi}$

- 1: Input data-set $\mathbf{X} \in \mathbb{R}^{n \times p}$.
 - 2: Define $\rho \in \mathbb{N} : \{1, \dots, f\}$ and $\chi \in \mathbb{R}^{1 \times f} : 0 < \chi_{1, \dots, f} < 1$ search values.
 - 3: $\mathbf{Y} = \mathbf{X}^\top \mathbf{X}$
 - 4: $[\bar{\mathbf{V}}, \mathbf{v}] = \text{eig}\{\mathbf{Y}\}$, where $\text{eig}\{\cdot\}$ returns the eigen-decomposition of its matrix argument.
 - 5: **for** $a = 1$ to e **do**
 - 6: **for** $b = 1$ to f **do**
 - 7: $\mathbf{w}^{(a,b)} = \mathbf{E}\{v_i(\bar{\mathbf{v}}_i \circ \bar{\mathbf{v}}_i) : \forall i = 1 \dots, \rho_e\}$
 - 8: $\mathbf{h}^{(a,b)} = \arg_i \left(w_i^{(a,b)} > \chi_f; i = 1, \dots, p \right)$
 - 9: Compute clustering algorithm over reduced data-set $\hat{\mathbf{X}}$ and obtain the ARI and NMI indexes ($\phi_{(a,b)}$ and $\psi_{(a,b)}$ respectively).
 - 10: **end for**
 - 11: **end for**
 - 12: Get the indices a and b for which Φ and Ψ are maximum and the respective parameters and relevance vector $\hat{\rho}, \hat{\mathbf{w}}$.
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3.3 Performed Accuracy of Reduced Heartbeat Feature Set

In order to assess the performance of the feature selection, the tuning and experimental setting of ρ and χ parameters is performed using Algorithm 1 with a kmeans clustering process (initial centroids provided by *max-min* algorithm) for each of the records obtaining a total of 18 relevance vectors. The reduced feature set is composed forming an average feature relevance from the whole database,

$$\mathbf{w}_\mu = \mathbf{E}\{\hat{\mathbf{w}}_i : \forall i = 1, \dots, 18\} \quad (3)$$

Now for the average relevance w_μ , features with relevance value higher than a given χ parameter ($0 < \chi < 1$) are to be considered to form the final reduced ensemble of features, this parameters gives us the possibility to eliminate some other features that were not that constant over the analysis, that is, features that were relevant only once or twice, might not be necessary if a more robust clustering technique is to be used in the final clustering process. Finally to analyze the feature selection effectiveness, Sensitivity and Specificity (Se and Sp) are computed for the results of kmeans clustering algorithm (KM)¹² over the final reduced data-sets.

4. RESULTS AND DISCUSSION

Initially, we set the search values $\rho = \{3, 4, 7, 11, 15, 19, 23\}$ and $\chi : \{0.82, 0.85, 0.88, 0.91, 0.94, 0.97\}$ and kmeans clustering is used over the heuristic search defined in algorithm 1. Table 3 shows the results of the optimal found parameters over each data-set, additionally the resulting number of features $\bar{p}$ is also given.

Table 3: $\hat{\rho}$ and $\hat{\chi}$ results with respect to ARI and NMI.

Rec	K	$\hat{\rho}$	$\hat{\chi}$	$\bar{p}$	ARI	NMI
104	3	11	0.91	23	0.8246	0.7324
106	2	7	0.82	62	0.9853	0.9603
107	2	3	0.94	8	0.9421	0.8840
109	2	7	0.91	28	0.8613	0.7507
114	2	3	0.88	24	1.0000	1.0000
116	2	7	0.94	28	0.9843	0.9545
119	2	3	0.97	16	1.0000	1.0000
203	2	23	0.88	62	0.8585	0.7238
205	2	7	0.97	17	1.0000	1.0000
208	3	3	0.82	36	0.9049	0.8369
210	3	7	0.94	11	0.8418	0.7241
214	2	7	0.94	17	0.7054	0.5980
215	2	3	0.88	18	0.9638	0.9179
217	4	7	0.97	7	0.9419	0.8384
221	2	15	0.97	18	0.9812	0.9530
228	2	3	0.97	9	0.7997	0.7024
231	2	3	0.97	7	0.9970	0.9905
233	2	19	0.85	123	0.7452	0.6663

Afterward, the average relevance vector is estimated in accordance to the procedure discussed in §3.3. Figure 1 shows the estimated average value of feature relevance over the whole ECG recording set. To make more clear the contribution, each considered heartbeat feature set is drawn with different color.

As seen, contrary to the assumption that the timing and morphology features ($x_1, \dots, x_9$) are better in discriminating the heartbeats classes, the set of considered spectral-based features are also competitive. Basically, some of derived from Fourier and DWT coefficients ($\{x_{10}, \dots, x_{14}\}$ and $\{x_{26}, \dots, x_{164}\}$, respectively), in average, reach a high relevance.

Now, having conformed the average relevance, the $\hat{\chi}$ parameter is set to $\hat{\chi} = 0.15$ and clustering is once again performed only with those features holding an average relevance value higher to $\hat{\chi}$. It must be remarked though, that the parameter setting is not a trivial matter, and visual inspection of the average achieved relevance was required, where in Figure 1 its clearly visible that there is a remarked gap between the number of features with relevances higher to 0.1 and 0.2 thus the value was manually set in the midpoint. It can be seen that some morphological features reach high relevance, yet the subset is composed mostly of spectral-based features (fourier, hermite, DWT and atom parameters). Table 4 shows the sensibility and specificity results for the most relevant features. It can be seen that such features represent a wide range of heartbeat types.

Figure 1: Estimated average value of feature relevance over the whole ECG recording set. (— $x_1, \dots, x_4$, — $x_5, \dots, x_9$, — $x_{10}, \dots, x_{25}$, — $x_{26}, \dots, x_{164}$, — $x_{165}, \dots, x_{75}$, — $x_{176}, \dots, x_{181}$).

Table 4: Sensitivity and Specificity Results per record.

Patient	Se_N	Sp_N	Se_L	Sp_L	Se_R	Sp_R	Se_V	Sp_V	Se_F	Sp_F	Se_f	Sp_f	Se_P	Sp_P
104	0.00	0.99									0.67	0.89	0.99	0.74
106	0.99	0.99					0.99	0.99						
107							0.89	1.00					1.00	0.89
109			0.99	0.28			0.28	0.99						
114	1.00	1.00					1.00	1.00						
116	0.99	0.99					0.99	0.99						
119	1.00	1.00					1.00	1.00						
203	0.98	0.91					0.91	0.98						
205	1.00	1.00					1.00	1.00						
208	1.00	0.95					0.94	0.99	0.82	0.98				
210	1.00	0.76					0.80	0.99						
214			1.00	0.62			0.62	1.00						
215	1.00	0.93					0.93	1.00						
217	1.00	0.91					0.85	1.00			0.38	0.98	0.99	1.00
221	1.00	0.97					0.97	1.00						
228	1.00	0.77					0.77	1.00						
231	1.00	0.99			0.99	1.00								
233	1.00	0.65					0.65	1.00						

5. CONCLUSIONS AND FUTURE WORK

This work performs an study of some literature reported features for ECG arrhythmia characterization and uses a feature selection procedure to assess heartbeat clustering into high performance. The feature selection is done over heuristic search of the optimal parameters according to clustering validity measures ARI and NMI, taking advantage of the selection scheme it can be seen that spectral based features are more suitable to separate a broader spectrum of heartbeats, in contrast with the most common temporal and morphological features. Additionally as a result of feature selection, not only the clustering performance is enhanced but also the computational burden is reduced.

Although different in terms of nature, morphological and spectral based features are both important in heartbeat clustering. However the spectral-based features also include temporal information, as the DWT coefficients and Atom parameters, so they become more relevant in terms of clustering separability. This fact prompts to search for a mixed set of both features types that better represent each class of heartbeats.

As future work, we attempt to carry out the evaluation of the extracted heartbeat feature sets by using a more complex optimization function allowing to include several clustering schemes exploring more elaborated relationships between projected and original feature spaces.

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