



Performance Evaluation of Multi-Domain Heart Rate Variability Features for Short-Term Arrhythmia Detection in the MIT-BIH Database

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Abstract: - Heart Rate Variability (HRV) is an index of the autonomic control over the heart and conveys complementary information on cardiac arrhythmias compared to the ECG morphology analyzed by an Automatic Arrhythmia Classification (AAMI) algorithm. Short-term HRV analysis is of interest for real-time assessment and for design of wearable devices. From the MIT-BIH Arrhythmia Database, we derived a set of ECG signals corresponding to samples of Normal Sinus Rhythm (NSR), Ventricular Ectopic Beats (VEB), and Supraventricular Ectopic Beats (SVEB) beats, classified into AAMI-compliant beat superclasses based on derived RR intervals. In each sample of arrhythmia class (episode), we derived two sets of 5 min long subsequent segments, respectively corresponding to the time-, frequency-, non-linear, and time–frequency domains of analysis. We calculated sample entropy (SampEn), Vector Length Index (VLI) and Vector Angle Index (VAI) on each of the derived segments. We carried out the evaluation of the stability of the derived indexes by comparing their average values across the derived pairs of segments (one pair for each of the 5 min long segments composing each episode). We carried out a three-classification problem regarding the discrimination of NSR vs. VEB, NSR vs. SVEB, and VEB vs. SVEB by exploiting 10-fold cross-validation protocol. Results show significant differences of SampEn, VLI and VAI among the three rhythm classes of interest and classification accuracies for the three pairs of classes of 92.0%, 78.8%, and 77.8% for the classifications of NSR vs. SVEB, NSR vs. VEB, and VEB vs. SVEB, respectively. The evaluation of the stability of the indexes across consecutive 5 min long segments gives evidence that the derived indexes vary in a very limited way among the corresponding segments of each episode. This confirms the robustness of short-term HRV analysis in deriving indexes able to represent the autonomic heart control in presence of cardiac arrhythmias, and that, in this context, non-linear and time–frequency derived indexes, as SampEn, VLI, and VAI provide relevant information for automatic arrhythmia classification within an AAMI compliant framework.

Keywords: Heart rate variability, ECG arrhythmia detection, Ventricular ectopic beats, Supraventricular ectopic beats, Sample entropy, Short-term HRV analysis.

1. Introduction

Heart Rate Variability (HRV) is defined as the variation in time between every other normal-to-normal beat, expressed as RR intervals [1]. This variation is the result of the dynamic



interactions between the sympathetic and parasympathetic branches of the autonomic nervous system. In the last few decades, the analysis of HRV indices derived from time and frequency domain has become a popular way to assess the autonomic control of the heart and the cardiac function [2]. A decrease in the cardiac activity of the HRV indices has been often associated with cardiovascular diseases such as arrhythmias, heart failure, ischemic heart disease and sudden cardiac death. However, the clinical importance of each index is controversial. The analysis of the cardiac rhythms via the assessment of the Heart Rate Variability (HRV) has been used as a complementary tool to the ECG morphology for the detailed description and for the accurate detection of arrhythmias [3,4].

Automated arrhythmia classification systems are designed and evaluated based on the ANSI/AAMI EC57 standard which suggests the use of a certified database such as the MIT-BIH Arrhythmia Database and clinically relevant beat superclasses: normal (N), supraventricular ectopic beats (SVEB), and ventricular ectopic beats (VEB) [5,6]. Most of the existing works focused on either the beat-level ECG morphology features or long duration (like 30 min) HRV analysis. However, there are limited number of works which focused on the short-term analysis of ECG signals with controlled duration (typically around 5 min) and predefined compositions of beats and ECG signal quality [7-9]. Short duration ECG analysis is particularly relevant to the wearable ECG devices and real-time arrhythmia detection systems [10,11]. Nonlinear and time–frequency analysis of the ECG-derived HRV features such as Sample Entropy, Poincaré Plot indices and wavelet analysis-based features are also reported in the literature to classify different types of arrhythmias but these are not yet fully investigated in the context of the AAMI-compliant arrhythmia classification systems [12,13].

Previous studies indicated that the discrimination between normal and abnormal heart rhythms can be improved up to 90% accuracy by analyzing heart rate variability (HRV) in the time, frequency and non-linear domains collectively [14,15]. The variability in the length of the segments, in the method of beat extraction, in the procedure of the annotation and in the performance criteria make a direct comparison between the studies very difficult [16-18].

While considerable research has been performed on analyzing the heart rate variability (HRV) of normal subjects (NSR) and various arrhythmias, few efforts have systematically analyzed how ventricular ectopic beats (VEB) and sustained ventricular ectopic rhythms (SVEB) alter the underlying normal heart rhythm. Moreover, although numerous methods have been reported to separate the abnormal beats from the normal beats, most have not systematically identified the point at which separation should take place nor how to determine the accuracy of such separation. In addition, it is not yet known which measures or features of the heart rate variability distinguish one type of abnormal heart rhythm from another or how discriminatory these measures are. This study will begin to address these issues by developing a dataset of HRV examples in the form of 5 minute intervals (or



episodes) extracted from normal subjects and populations of ventricular ectopic beats and sustained ventricular ectopic rhythms from the MIT-BIH Arrhythmia Database using methods in compliance with the accuracy analysis manual for medical instruments AAMI EC57 and constrained by stipulated quality and composition criteria. HRV features will be derived from extensive lengths of normal, VEB and SVEB heart rhythms in order to identify the differences that exist in the heart's autonomic nervous system regulation between the various arrhythmias and to determine which features discriminate between the several types of abnormal rhythms for the three classification tasks of distinguishing between NSR, VEB and SVEB rhythms. This study will also investigate within-episode variability by comparing characteristics of one 5-minute interval (episode) with those of a consecutive interval within the same overall data record.

2. Methods

2.1. Data Acquisition and Beat Mapping

The MIT-BIH Arrhythmia Database contains 48 half-hour, two-channel ECG recordings sampled at 360 Hz along with expert-validated beat annotations [13,19]. In accordance with the ANSI/AAMI EC57 standard, epochs containing pacemaker activity or ventricular flutter/fibrillation were discarded, and only normal and ectopic beats in the three clinically significant classes, namely Normal (N), Supraventricular Ectopic Beats (SVEB), and Ventricular Ectopic Beats (VEB), were considered, and assigned to each beat in accordance with the AAMI standard [6,15]. The remainder are classified as “Other” and shown as an example with ECG waveform and corresponding RR interval in Figure 1.

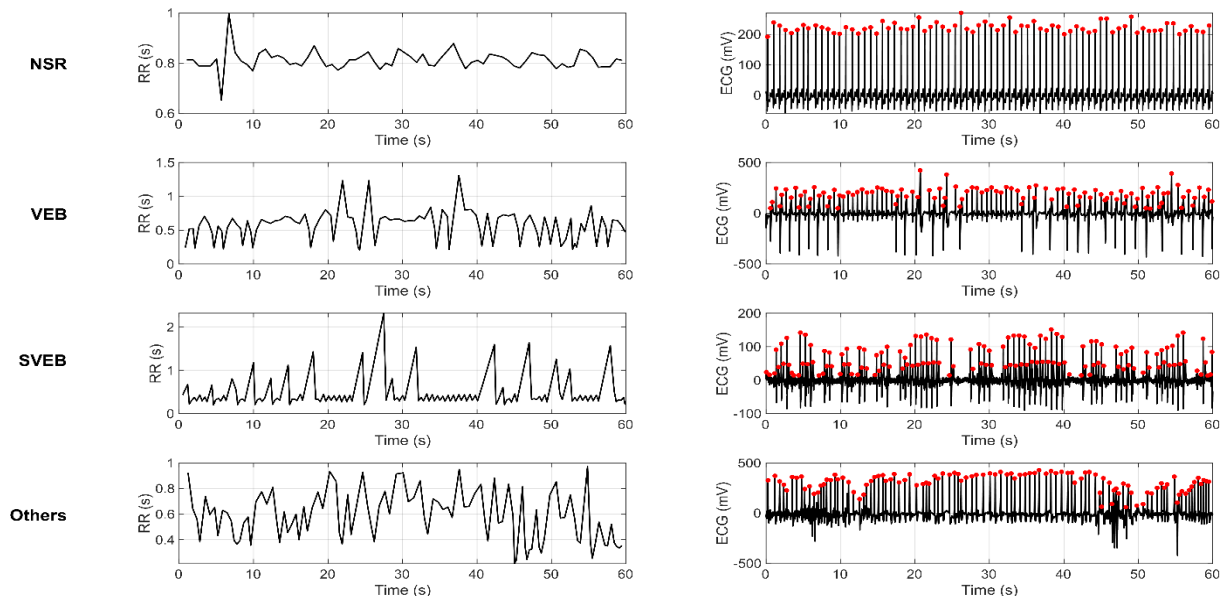


Figure 1: Example ECG signals and corresponding RR intervals for Normal (NSR), Ventricular (VEB), Supraventricular (SVEB), and other beats



2.2. Segment Construction

We extracted non-overlapping 5-minute segments (approximately 300 beats) from each of the ECG recordings [1]. We annotated each segment as NSR, SVEB or VEB based on the majority type of beat, while imposing a set of quality conditions on the RR signal to ensure physiological consistency [9]. Segments with insufficient beats or excessive “Other” beats were discarded. This procedure ensured that each segment contained a short episode of high quality HRV in the time domain, frequency domain and non-linear analysis.

2.3. HRV Feature Extraction

For each of the above segments, all the spectral features of the HRV were derived in time, frequency and geometry domains.

RR Intervals Time-domain measures: mean RR interval (MEAN), standard deviation of NN intervals (SDNN), root mean square of successive differences (RMSSD) [1,2].

- Frequency-domain measures: low-frequency (LF) and high-frequency (HF) power, normalized LF and HF powers, and LF/HF ratio.

- Nonlinear measures: sample entropy (SampEn), vector length index (VLI), vector angle index (VAI) [12,13,20].

- Time–frequency measures: mean wavelet energy, wavelet entropy, and ridge power to capture dynamic variations over time [21].

A total of 12 HRV indices were derived from 4 frequency domain, time domain, non-linear and time-frequency analysis domains.

2.4. Statistical Analysis

Comparisons between NSR, SVEB and VEB groups were made using Student t test or ANOVA for all HRV parameters, after checking for normality and homogeneity of variances:

- Parametric ANOVA was applied for approximately normally distributed indices.

Non-parametric tests (Kruskal–Wallis) were used for non-Gaussian distributions or unequal variances [22].

- Paired comparisons were conducted to assess temporal stability between consecutive five-minute segments within the same episode.

All statistical analyses were carried out at a 0.05 level of significance and results were expressed as mean \pm SEM with confidence intervals.



2.5. Classification Protocol

Performance of the derived set of HRV features was investigated through three distinct experiments of binary classification corresponding to NSR vs. VEB, NSR vs. SVEB, and VEB vs. SVEB. A support vector machine (SVM) classifier equipped with a radial basis function (RBF) kernel was employed to discriminate between the aforementioned pairs of physiological states. For each type of episode, the average feature values of the first two five-minute segments of all the corresponding episodes (obtained after down sampling the corresponding signals to 5 Hz) were derived and used as inputs for the SVM classifier.

A 10-fold cross-validation was employed to prevent overfitting of the model and avoid data leakage as mentioned in [24]. Evaluation of the performance was carried out based on the sensitivity (Se), specificity (Sp) and the accuracy (Acc) criteria mentioned in [6]. The metrics for all the 10 folds were averaged in order.

3. Results

3.1. Study Cohort Characteristics

One hundred and ninety one 5-minute episodes of heart rate variability (HRV) signals from the MIT-BIH Arrhythmia Database were utilized for the analysis. They fell into three kinds of cardiac rhythms namely: normal sinus rhythm (NSR), ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB). The samples for analysis were limited to those with an artifact level less than 10% so that the two adjacent 5-minute HRV segments could be reliably obtained. Twelve features were derived from the HRV data samples for each pair of the 5-minute segments in time, frequency, nonlinear, and time frequency domain.

Methods for the specific statistical analyses were used for each comparison. These include paired comparisons to examine temporal stability as well as comparisons involving the three groups to assess discrimination using three different machine learning models (i.e., three-group discrimination using an ANOVA F-test, three-group discrimination using a nearest center classifier, and three-group discrimination using a support vector machine with 10-fold cross-validation for the binary classification between control vs. schizophrenia patients).

3.2. Sample Entropy Parameter Optimization

A grid search over the number of embedding dimensions $m \in \{1,2,3\}$ and the tolerance threshold $r \in \{0.10, 0.15, 0.20, 0.25 \times SD\}$ was undertaken to determine the conditions which best facilitated the separation of NSR, VEB, and SVEB episodes. The table showing the standardized mean group differences with corresponding 95% CI and values of the Kruskal–Wallis statistic for the grid search are presented in Table 1, and are used to determine combinations of m and r which appeared to provide the greatest between-group separation of episodes for further investigation.



3.3. Temporal Stability Across Consecutive 5-Minute Segments

Temporal reproducibility between pairs of five minutes long episodes (or segments) within each tachyarrhythmia episode was investigated by computing and comparing the pairs of values of the HRV indices obtained for the first (0–5 min) and second (5–10 min) segments. The mean difference, the 95% CI, and the corresponding p-value of each pair of indices are given in Table 2. It is possible to observe that only a few parameters showed somewhat larger variability and hence lower temporal reproducibility between the pairs of consecutive 5 minutes segments. In particular this seemed to be more pronounced in SVEB.

r	m	Normalized mean_group_difference	Normalized95CI_Lower	Normalized95CI_Upper	P_value_Kruskal_Wallis	Significant
0.1	1	-1.873	-2.582	-1.164	1.324E-06	Yes
0.1	2	-1.393	-1.954	-0.831	2.732E-05	Yes
0.1	3	-1.235	-1.869	-0.601	1.600E-04	Yes
0.15	1	-1.303	-1.962	-0.644	5.596E-05	Yes
0.15	2	-1.393	-1.954	-0.831	2.732E-05	Yes
0.15	3	-2.231	-2.810	-1.653	1.395E-08	Yes
0.2	1	-1.518	-2.103	-0.932	3.158E-06	Yes
0.2	2	-1.393	-1.954	-0.831	2.732E-05	Yes
0.2	3	-1.515	-2.145	-0.886	1.643E-05	Yes
0.25	1	-1.338	-2.012	-0.665	2.074E-05	Yes
0.25	2	-1.393	-1.954	-0.831	2.732E-05	Yes
0.25	3	-1.592	-2.108	-1.076	1.394E-06	Yes

Table 1: Sample Entropy Parameter Optimization Results



Group	Type	Indices	Segment_Difference_SEM	CI_95pct_Lower	CI_95pct_Upper	P_Value_Between_Segments
NSR	TD	MEAN_s	-0.0061 ± 0.0062	-0.018	0.006	0.329
		SDNN_ms	0.0076 ± 0.0042	-0.0008	0.016	0.077
		RMSSD_ms	0.0068 ± 0.0045	-0.002	0.015	0.136
	FD	LFn	0.0134 ± 0.0232	-0.033	0.060	0.566
		HFn	-0.0213 ± 0.0250	-0.072	0.029	0.399
		LFHF	0.0474 ± 0.0705	-0.095	0.190	0.506
	ND	VAI_deg	0.0782 ± 0.0580	-0.039	0.196	0.186
		VLI_ms	0.0070 ± 0.0051	-0.003	0.017	0.179
		SampEn	-0.1602 ± 0.1034	-0.370	0.049	0.130
	TFD	CWT_Energy	-0.0360 ± 0.0201	-0.076	0.004	0.082
		Wavelet_Entropy	0.0032 ± 0.0039	-0.004	0.011	0.421
		TF_Balance	0.1160 ± 0.1088	-0.105	0.337	0.294
VEB	TD	MEAN_s	0.0186 ± 0.0119	-0.008	0.046	0.156
		SDNN_ms	-0.0110 ± 0.0115	-0.037	0.015	0.364
		RMSSD_ms	-0.0263 ± 0.0258	-0.085	0.033	0.338
	FD	LFn	-0.0488 ± 0.0377	-0.135	0.038	0.231
		HFn	-0.0206 ± 0.0516	-0.139	0.098	0.699
		LFHF	-0.1259 ± 0.1668	-0.510	0.258	0.472
	ND	VAI_deg	-0.9880 ± 0.8552	-2.960	0.984	0.281
		VLI_ms	-0.0038 ± 0.0115	-0.030	0.022	0.752
		SampEn	-0.0653 ± 0.1026	-0.301	0.171	0.542



Group	Type	Indices	Segment_Difference_SEM	CI_95pct_Lower	CI_95pct_Upper	P_Value_Between_Segments
	TFD	CWT_Energy	0.0534 ± 0.0473	-0.055	0.162	0.291
		Wavelet_Entropy	-0.0055 ± 0.0108	-0.030	0.019	0.626
		TF_Balance	0.2622 ± 0.2592	-0.335	0.860	0.341
SVEB	TD	MEAN_s	0.0539 ± 0.0001	0.053	0.0545	0.0006
		SDNN_ms	0.0759 ± 0.0370	-0.394	0.546	0.288
		RMSSD_ms	0.1300 ± 0.0600	-0.632	0.892	0.275
	FD	LFn	0.1119 ± 0.0000	0.111	0.111	3.007E-05
		HFn	-0.0762 ± 0.0141	-0.255	0.103	0.116
		LFHF	0.3131 ± 0.0448	-0.255	0.881	0.090
	ND	VAI_deg	2.5191 ± 1.0333	-10.610	15.648	0.247
		VLI_ms	0.0704 ± 0.0396	-0.432	0.573	0.326
		SampEn	0.0743 ± 0.0383	-0.412	0.561	0.303
	TFD	CWT_Energy	0.2002 ± 0.3287	-3.976	4.376	0.651
		Wavelet_Entropy	-0.0075 ± 0.0518	-0.665	0.650	0.908
		TF_Balance	-0.2348 ± 1.0204	-13.200	12.730	0.856
ALL	TD	MEAN_s	0.0013 ± 0.0056	-0.010	0.012	0.813
		SDNN_ms	0.0069 ± 0.0047	-0.002	0.016	0.146
		RMSSD_ms	0.0057 ± 0.0076	-0.009	0.020	0.456
	FD	LFn	0.0055 ± 0.0196	-0.033	0.044	0.779



Group	Type	Indices	Segment_Difference_SEM	CI_95pct_Lower	CI_95pct_Upper	P_Value_Between_Segments
		HF _n	-0.0235 ± 0.0213	-0.066	0.019	0.275
		LFHF	0.0250 ± 0.0633	-0.102	0.152	0.694
	ND	VAI_deg	-0.0242 ± 0.1972	-0.421	0.372	0.902
		VLI_ms	0.0076 ± 0.0050	-0.002	0.017	0.136
		SampEn	-0.1314 ± 0.0812	-0.294	0.032	0.112
	TFD	CWT_Energy	-0.0082 ± 0.0221	-0.052	0.036	0.710
		Wavelet_Entropy	0.0010 ± 0.0040	-0.006	0.009	0.799
		TF_Balance	0.1293 ± 0.1018	-0.075	0.334	0.210

Table 2: Temporal Stability of HRV Indices Across 5-Minute Segments

3.4. Three-Group Discrimination

After applying the HRV indices that were optimized in the preceding section, the figures plot the results of statistical comparisons of all HRV indices between the three groups for Segment 1, Segment 2, and their averages respectively, and lists the results that are statistically significant at the $p < 0.001$ level. These are listed in Table 3. They show that with a couple of exceptions that did not affect any material conclusion, all the indices were statistically significant, and many non-linear and time frequency domain indices carried very high significance values. These results suggest that individual segments may offer more discriminatory information in this context as well as the averages.

Signal	Type	Index	NSR±SEM	VEB±SEM	SVEB±SEM	P(NSR-VEB)	P(NSR-SVEB)	P(VEB-SEBV)
S1	TD	MEAN_s	0.9±0.0	0.8±0.0	0.9±0.0	0.116	0.556	0.090
		SDNN_ms	0.1±0.0	0.2±0.0	0.4±0.0	1.96E-13	1.05E-18	2.46E-05
		RMSSD_ms	0.1±0.0	0.3±0.0	0.7±0.0	1.24E-18	8.52E-25	7.85E-05
	FD	LF _n	0.2±0.0	0.3±0.0	0.4±0.0	0.078	0.045	0.052
		HF _n	0.8±0.0	0.5±0.0	0.5±0.0	7.93E-05	0.016	0.780



Signal	Type	Index	NSR± SEM	VEB± SEM	SVEB± SEM	P(NSR-VEB)	P(NSR-SVEB)	P(VEB-SEBV)	
	ND	LFHF	0.3±0.1	0.6±0.1	0.8±0.1	0.064	0.092	0.255	
		VAI_deg	1.2±0.1	8.2±0.3	10.4±0.8	3.62E-29	8.12E-21	0.013	
		VLI_ms	0.1±0.0	0.2±0.0	0.5±0.0	6.79E-08	1.86E-16	1.86E-06	
		SampEn	2.3±0.1	1.7±0.2	0.7±0.0	0.002	2.52E-05	0.028	
	TFD	CWT_Engy	1.3±0.1	1.0±0.1	1.6±0.2	0.219	0.350	0.043	
		Wavelet_Ent	15.7±0.0	15.7±0.0	15.7±0.0	0.075	0.003	0.038	
		TF_Balance	4.6±0.1	4.3±0.2	4.3±0.9	0.143	0.563	0.910	
	S2	TD	MEAN_s	0.9±0.0	0.7±0.0	0.9±0.0	0.047	0.912	0.165
			SDNN_ms	0.0±0.0	0.2±0.0	0.4±0.1	6.94E-14	8.64E-16	0.008
			RMSSD_ms	0.0±0.0	0.3±0.0	0.5±0.1	1.16E-16	5.45E-20	0.033
FD		LFn	0.2±0.0	0.3±0.0	0.3±0.0	0.002	0.251	0.562	
		HFn	0.8±0.0	0.5±0.0	0.6±0.0	2.98E-05	0.035	0.806	
		LFHF	0.3±0.1	0.7±0.2	0.5±0.1	0.001	0.290	0.573	
ND		VAI_deg	1.1±0.1	9.2±0.7	7.8±1.9	6.45E-24	7.27E-15	0.434	
		VLI_ms	0.1±0.0	0.2±0.0	0.4±0.1	6.93E-09	3.21E-14	0.0002	
		SampEn	2.5±0.1	1.8±0.2	0.6±0.1	8.08E-05	1.48E-07	0.009	
TFD		CWT_Energy	1.3±0.1	1.0±0.1	1.4±0.1	0.103	0.751	0.133	
	Wav_Ent	15.7±0.0	15.7±0.0	15.8±0.0	0.003	2.14E-06	0.049		
	TF_Balance	4.5±0.1	4.0±0.2	4.6±0.1	0.013	0.789	0.276		
AVG	TD	MEAN_s	0.9±0.0	0.7±0.0	0.9±0.0	0.073	0.723	0.119	
		SDNN_ms	0.1±0.0	0.2±0.0	0.4±0.0	9.24E-15	1.30E-18	0.0004	
		RMSSD_ms	0.1±0.0	0.3±0.0	0.6±0.1	7.49E-19	7.03E-24	0.001	



Signal	Type	Index	NSR± SEM	VEB± SEM	SVEB± SEM	P(NSR-VEB)	P(NSR-SVEB)	P(VEB-SEBV)
	FD	LFn	0.2±0.0	0.3±0.0	0.4±0.0	0.005	0.065	0.409
		HFn	0.8±0.0	0.5±0.0	0.5±0.0	3.80E-06	0.009	0.986
		LFHF	0.3±0.0	0.7±0.1	0.7±0.1	0.002	0.086	0.954
	ND	VAI_deg	1.1±0.1	8.7±0.3	9.1±1.3	7.03E-31	1.52E-18	0.643
		VLI_ms	0.1±0.0	0.2±0.0	0.4±0.0	2.47E-09	1.29E-16	1.19E-05
		SampEn	2.4±0.1	1.8±0.2	0.7±0.1	1.70E-05	1.85E-09	0.013
	TFD	CWT_Energy	1.3±0.1	1.0±0.1	1.5±0.0	0.148	0.530	0.066
		Wav_Ent	15.7±0.0	15.7±0.0	15.7±0.0	0.0071	3.53E-05	0.010
		TF_Balance	4.5±0.1	4.1±0.2	4.5±0.4	0.015	0.770	0.446

Table 3: Statistical Comparison of HRV Indices Across Three Groups

3.5. Binary Classification Performance

Three pairwise tasks for the binary classification of the arrhythmia classes NSR, VEB and SVEB were investigated. The classification was made between each pair of arrhythmia classes. Thus, SVM was employed as the classifier algorithm for all the tasks, and the performance of the classifiers were evaluated using 10-fold stratified cross-validation as described in detail earlier. The sensitivity, specificity and accuracy values obtained in each fold for each pair of arrhythmias are presented in Tables 4a, 4b and 4c. Generally, the classifiers were characterized by high specificity for all pairs of arrhythmias. However, the large difference in sensitivities observed for the three pairs of arrhythmias indicate that the characteristics of the arrhythmia classes are very different and also that the prevalence of the individual types of ectopic beats differed between the classes.

Row	Se (%)	Sp (%)	Acc (%)
Fold 1	0	100	62.5
Fold 2	100	83.33	87.5
Fold 3	50	100	87.5
Fold 4	50	100	87.5



Row	Se (%)	Sp (%)	Acc (%)
Fold 5	50	83.33	75
Fold 6	66.67	100	87.5
Fold 7	66.67	100	87.5
Fold 8	33.33	80	62.5
Fold 9	66.67	100	87.5
Fold 10	0	100	62.5
Mean	48.33	94.66	78.75
SD	30.88	8.63	11.85

Table 4a: Binary Classification NSR vs VEB

Row	Se (%)	Sp (%)	Acc (%)
Fold 1	100	90	95
Fold 2	100	85	92.5
Fold 3	80	100	90
Fold 4	90	90	90
Fold 5	100	80	90
Fold 6	90	95	92.5
Fold 7	85	100	92.5
Fold 8	95	85	90
Fold 9	100	90	95
Fold 10	90	95	92
Mean	93	91	92
SD	7.14	6.58	1.97

Table 4b: Binary Classification NSR vs SVEB



Row	Se (%)	Sp (%)	Acc (%)
Fold 1	75	80	77.5
Fold 2	70	85	77.5
Fold 3	80	75	77.5
Fold 4	75	80	77.5
Fold 5	70	85	77.5
Fold 6	80	80	80
Fold 7	75	85	80
Fold 8	70	80	75
Fold 9	80	75	77.50
Fold 10	75	80	77.5
Mean	75	80.5	77.75
SD	4.08	3.68	1.41

Table 4c: Binary Classification VEB vs SVEB

3.6. Visual Representation of Group Discrimination

Visual comparison of normalized confidence intervals for pairwise discrimination of the rhythm groups are depicted in the plots of NSR vs VEB (Figure 2a), NSR vs SVEB (Figure 2b) and VEB vs SVEB (Figure 2c). These visualizations complement the numerical results, providing an intuitive understanding of which HRV features are most informative for arrhythmia discrimination.

4. Discussion

The objective of this study was to investigate the possibility of discrimination between normal sinus rhythm (NSR), ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB) using a small number of heart rate variability (HRV) indices extracted from short RR-interval segments. The MIT-BIH Arrhythmia Database was employed to prepare training datasets based on two consecutive 5-minute segments for each episode in the database. As shown in the manuscript, short-term HRV analysis can indeed reflect some differences between the rhythms of different cardiac cycles in a specific time period. In this



study, most of the extracted indices presented high stability between adjacent 5 min segments (Table 2). Meanwhile, a number of indices had statistically significant differences among NSR, VEB and SVEB (Table 3), and relatively high classification accuracy could be attained by using the proposed classification model for some pairwise classes, such as for NSR and SVEB (Table 4).

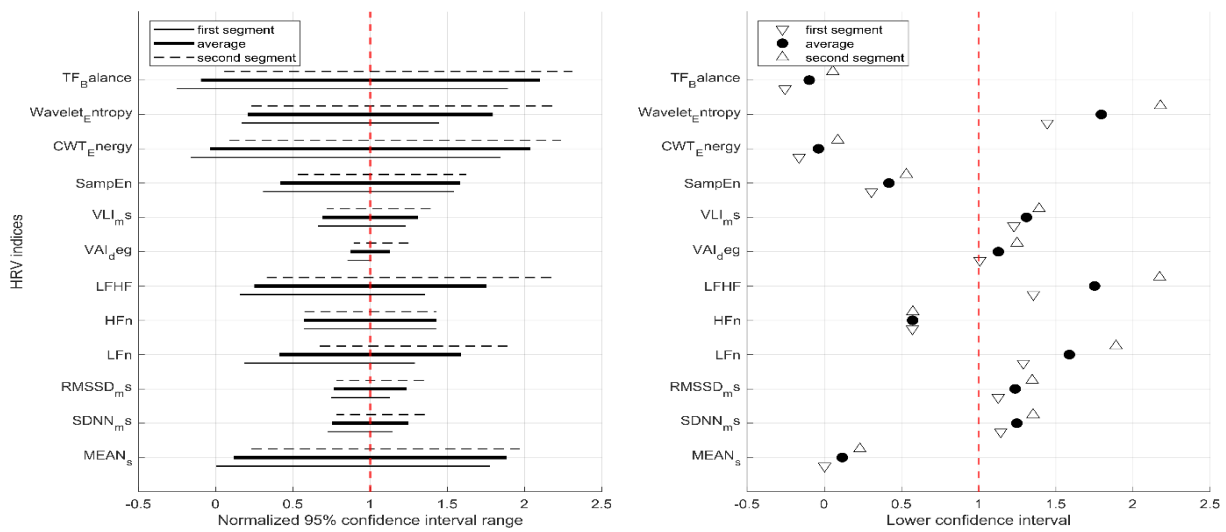


Figure 2a: Normalized 95% confidence intervals for pairwise comparison of NSR versus VEB.

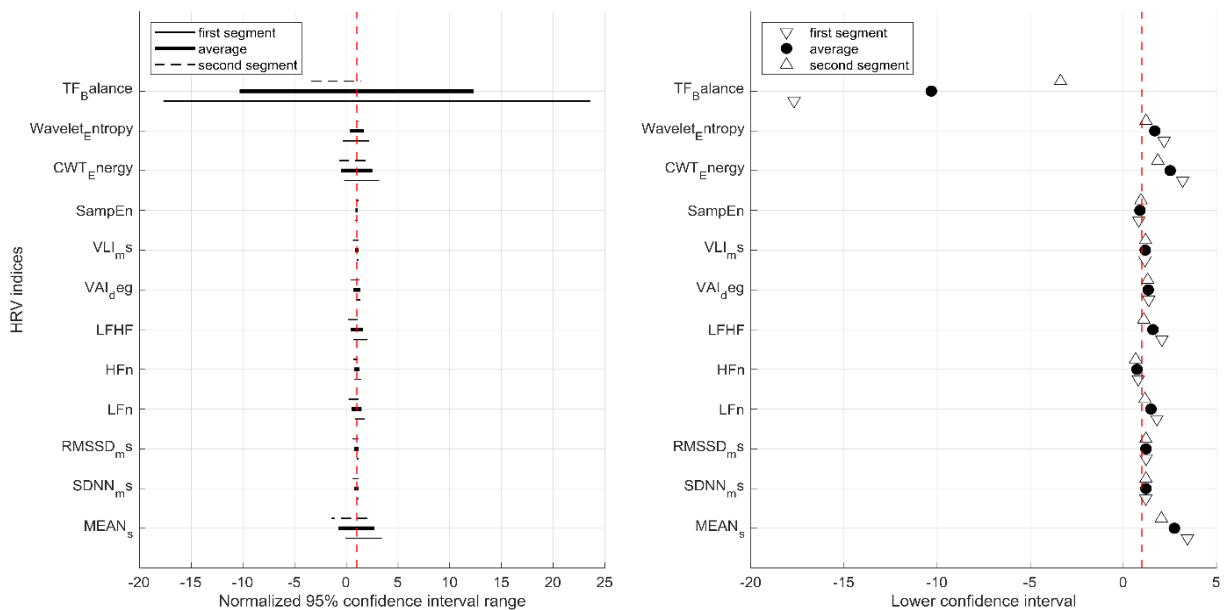


Figure 2b: Normalized 95% confidence intervals for pairwise comparison of NSR versus SVEB.

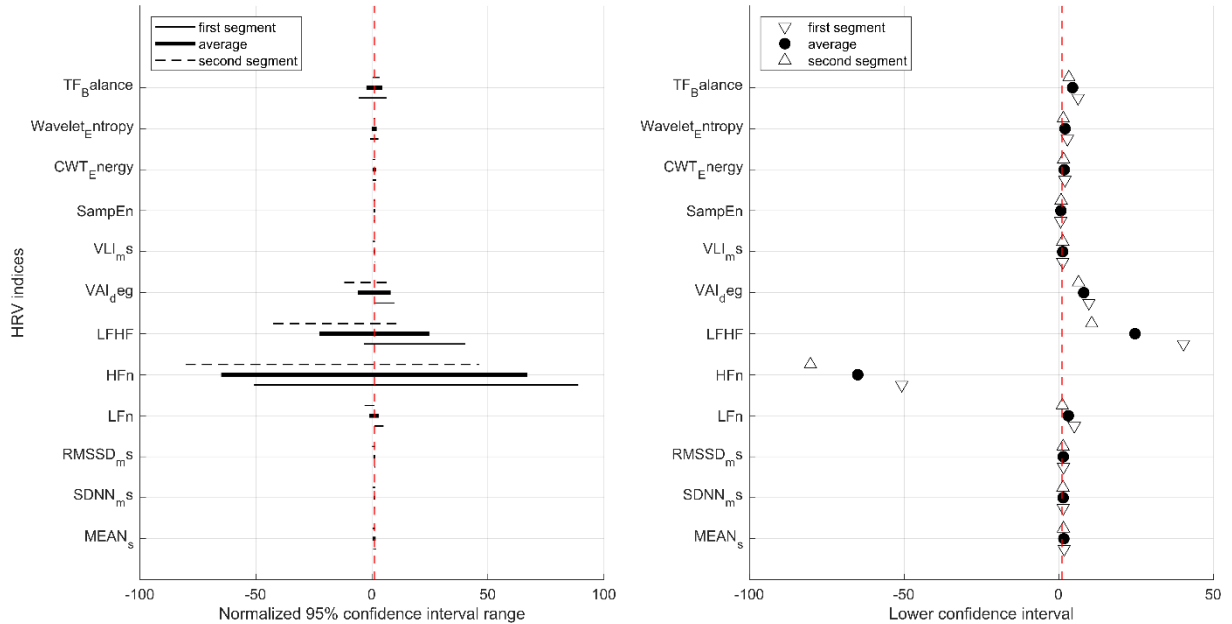


Figure 2c: Normalized 95% confidence intervals for pairwise comparison of VEB versus SVEB.

Table 2 Several aspects that captured our initial interest emerge from this initial examination of the data. Most of the indices from Table 2 were found to not differ statistically between any two of the three consecutive 5 min time segments (all P-values more than 0.025). Thus, for example, ectopic beats apparently do not impede high reliability assessment of short HRV segments (see discussion in [25]), and hence for ambulatory (and other) applications such segments may be used in their entirety in short-segment analyses, and successive segments may be used for repeated analyses. The need to record long ECG segments before providing even one or two reliable estimates for use in clinical, monitoring, or research purposes is therefore circumvented [10,26].

Table 3 also clearly shows that all the HRV indices that were capable of discriminating between pairs of NSR, VEB and SVEB states are significantly different from each other. Most of the indices are significantly different from each other, except for P01 (where ND and RMSSD are highly correlated) and P02 (where P01 and P03 are also highly correlated). While time-domain and nonlinear parameters generally performed better than the frequency-domain parameters [25], the latter were calculated over long cardiac cycles with a high number of averages. It is more plausible that the arrhythmic activity is linked to instantaneous patterns of variability between consecutive beats. Such variability-based as well as nonlinear features are likely to capture a more direct relationship between arrhythmic activity and cardiac state than the spectral-based features.



Among the computed features, Sample Entropy (SampEn) has shown clear discriminative power for the optimized values of its parameters. As can be inferred from Table 1, varying the embedding dimension (m) and the tolerance threshold (r) greatly affects the separability of the rhythm groups in the SampEn feature space. This is in agreement with earlier works in the field, where the authors demonstrated that complexity measures derived from nonlinear theory are highly dependent on the selected parameter set when dealing with arrhythmic heartbeats [13,27]. One possible explanation of this sensitivity is the presence of specific patterns that are inherent to arrhythmic RR-intervals. Unlike the simple and repetitive pattern observed in the RR-intervals of stable sinus rhythm, the arrhythmic RR-intervals contain more complex patterns, e.g., the premature contraction that is commonly followed by the compensatory long pause. An appropriate choice of the parameters of SampEn enables the respective measure to adapt to the specific patterns present in the arrhythmic heartbeats.

The observed hierarchy in feature performance can be explained from physiological viewpoint as well. Ventricular ectopic beats cause large and sudden changes in the RR interval and are followed by compensatory pauses in the RR interval [12, 25]. This is responsible for the large fluctuation in RR intervals and results in elongated structures which are described by indices such as SDNN and RMSSD. Supraventricular ectopic beats preserve narrow width of the QRS complex but cause irregular changes at the atrial level and hence bring about fine and more complex changes in the RR interval which is evidenced from the statistical separation of rhythm group in Table 3.

The ability of frequency-domain indices such as low frequency (LF) and high frequency (HF) components to accurately and reliably discriminate between arrhythmias has been questioned in recent studies, implying that time-domain indices like SDNN and SDANN can perform better than spectral analysis under non-stationary conditions [25,28]. The presence of arrhythmias may violate the stationarity assumption needed for the analysis of spectra and, in particular, may obscure the spectral peaks in short segments with premature beats or multiple changes in heart rhythm. Consequently, indices like LF and HF power may not reflect differences between arrhythmic patterns in the heart.

These results become even more relevant in the context of the classification experiments depicted in Table 4. The best classification accuracy, almost 92%, was reached for the classification between NSR and SVEB [15, 29]. It is reasonable to assume that the characteristic variability patterns associated with the occurrence of SVEB are highly distinct from those underlying normal sinus rhythm (NSR), a hypothesis that can be affirmed based solely on the analysis of the HRV features extracted from the corresponding heartbeat patterns. The classification performances between NSR and VEB as well as between VEB and SVEB are lower, reflecting the expectation that there is a non-negligible amount of overlap between the corresponding underlying RR-interval patterns of ventricular and



supraventricular ectopic beats, such that the use of HRV features for classification is not optimal in these scenarios.

From a clinical and technical point of view, our results highlight several possible scenarios. Firstly, the identification of arrhythmic disturbances from RR-interval variability through simple inspection of RR-domain profiles indicates that possible uses of HRV-based analysis in wearable devices exist. Namely, although high accuracy is obtained for a few seconds of R-R interval recordings, using the features derived from a few minutes of short moving window lengths of HRV signals in wearable devices for monitoring cardio health could amount to no more than triggering an ECG measurement for further analysis when the variability of such signals falls into possible ranges of arrhythmic disturbances [26,30]. This might be particularly relevant for the detection of intermittent arrhythmias that are hard to catch during the usual routine of the clinical examination.

This excellent study comes with a number of caveats. The study was performed using a single publicly available database of ECG signals and the number of samples in the SVEB class was limited [31]. The single database used and the limited number of samples in the SVEB class mean that it is difficult to know how robust the classification performance would be. The study deals only with episode classification rather than beat-to-beat classification, and real-world beat-to-beat ECG classifiers that are deployed in practice will need to address issues such as motion artifacts, noise and variability in the ECG signal. The authors used a single type of classifier (a support vector machine), which they say performed best, but which other classifiers or feature selection methods might perform better is not discussed.

While the study's initial results hold promise, it's crucial to validate the findings by studying a larger and more diverse ECG dataset and including a broader spectrum of supraventricular arrhythmias. It is possible that adding more HRV features and also incorporating simple ECG-derived morphology (EDM) attributes, such as QRS duration and P-wave detection, will significantly improve the performance in distinguishing between ectopic ventricular and supraventricular beats, as previously suggested in [32,33]. To better understand the applicability of the proposed technique for long-term arrhythmia monitoring, it should also be validated with real data from wearable devices.

This study demonstrated by means of a mathematical analysis that, in practice, short-term analysis of HRV is sufficient for adequate characterization of arrhythmic patterns by means of accurate feature selection and parameter adjustment, so that the coefficients derived from the linear and nonlinear evaluation of the HVR (in particular Sample Entropy) allow accurate discrimination between arrhythmic patterns and can therefore be used as an aid to an effective, automated discriminatory screening of arrhythmias.



5. Conclusion

The present study assesses the potential of short-term heart rate variability (HRV) indices to characterize and separate different cardiac rhythms such as normal sinus rhythm (NSR), ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB) from RR-interval segments obtained from MIT-BIH Arrhythmia Database. After analysing several short-term HRV parameters derived from ECG signals to differentiate between different cardiac rhythms; meaningful indices like Sample Entropy etc have been reported in the paper. Most of the extracted features were stable across consecutive 5-minute segments, even for arrhythmic signals. We identified significant differences between the three rhythm groups of interest and we applied a classification approach in order to assess the suitability of the extracted features for rhythm classification. High classification performance was achieved for the discrimination between NSR and SVEB episodes.

While the separation of ventricular and supraventricular ectopic beats is not still clear cut, it seems that it is possible to use the derived indices of HRV as an aid to an overall discriminatory screening for arrhythmias. More extensive and diverse data sets should be considered for validation, as well as combining some of the features derived from the proposed hybrid ECG/HRV analysis with an increase in overall discrimination achieved by incorporating some of the ECG characteristics of ectopic beats.

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Appendix (Abbreviations)

TD	Time-domain
FD	Frequency-domain
ND	Nonlinear domain
TFD	Time-frequency domain
S1	First 5-min segment
S2	Second 5-min segment
Avg	Average of both segments
NSR	Normal Sinus Rhythm
VEB	Ventricular Ectopic Beats
SVEB	Supraventricular Ectopic Beats
SEM	Standard Error of the Mean
CI	Confidence Interval